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ABSTRACT

Perceptual-motor and cognitive processes whereby people perform multiple concurrent tasks have been studied through an overlapping-tasks procedure in which two successive choice-reaction tasks are performed with a variable interval (stimulus onset asynchrony, or SOA) between the beginning of the first and second tasks. The increase in subjects' reaction times (RTs), called the psychological refractory-period (PRP) effect, for Task 2 reveals basic characteristics of multiple-task performance. In this report, quantitative computational models are formulated to explain and predict the PRP effect and related phenomena on the basis of the Executive Process-Interactive Control (EPIC) information-processing architecture, which is a theoretical framework for precisely modeling human performance under representative single-task and multiple-task conditions. (Kieras & Meyer, 1994, Tech. Report TR-94/ONR-EPIC-1). Computer simulations suggest that the PRP effect may stem from subjects' task strategies and limitations on their peripheral perceptual-motor resources, rather than from a cognitive decision or response-selection "bottleneck." The goodness-of-fit between simulated and empirical data documents the EPIC architecture's utility for understanding and characterizing human multiple-task performance. (Contains 105 references and 16 figures.)
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EPIC Computational Models of Psychological Refractory Period Effects in Human Multiple-Task Performance

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EPIC Computational Models of Psychological Refractory-Period Effects in Human Multiple-Task Performance[1]

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Abstract

Perceptual-motor and cognitive processes whereby people perform multiple concurrent tasks have been studied through an overlapping-tasks procedure. During this procedure, two successive choice-reaction tasks are performed with a variable interval (stimulus onset asynchrony, or SOA) between the beginning of the first and second tasks. Subjects' reaction times (RTs) for Task 2 are typically greater after very short SOAs. The RT increase, called the *psychological refractory-period (PRP) effect*, reveals basic characteristics of multiple-task performance. The present report, quantitative computational models are formulated to explain and predict the PRP effect together with other related phenomena on the basis of the EPIC information-processing architecture, a theoretical framework for precisely modeling human performance under representative single-task and multiple-task conditions (Kieras & Meyer, 1994, Tech. Report TR-94/ONR-EPIC-1). Computer simulations with these models suggest that the PRP effect may stem from subjects' task strategies and limitations on their peripheral perceptual-motor resources, rather than from a cognitive decision or response-selection "bottleneck." The goodness-of-fit between simulated and empirical data documents the EPIC architecture's utility for understanding and characterizing human multiple-task performance.

1. Introduction

Ever since experimental psychology began, researchers have studied the extent to which people can perform multiple tasks at the same time (e.g., James, 1890; for reviews, see Gopher & Donchin, 1986; Norman, 1976).[2] The enduring hope has been that these studies would yield deep insights into the relationships among stages of information processing such as stimulus perception, response selection, and movement production. When this prospect has been pursued experimentally, it has typically led to the conclusion that during the performance of one task, some processing stages required for other concurrent tasks are temporarily impeded or precluded. Indeed, the received wisdom harks all the way back to Biblical times, where in the

[1] This is a revised and expanded version of a paper presented at the meeting of the Psychonomic Society, St. Louis, MO (Meyer & Kieras, 1992). The authors gratefully acknowledge funding from the United States Office of Naval Research for the present research (ONR Grant N00014-92-J-1173). We especially appreciate comments and support provided by Terry Allard, Susan Chipman, and Harold Hawkins of the ONR.

[2] As used here, the term "task" refers to a distinct transformation that people must make from some ensemble of physical stimulus inputs to some ensemble of physical response outputs on the basis of a systematic stimulus-response mapping. Under this definition, a particular situation would involve multiple tasks if it requires dealing with two (or more) such mappings, and the transformation from the stimuli to the responses of each mapping can, in principle, occur without reference to the other mappings (i.e., the tasks are modular and can each be performed alone). For example, two tasks might consist of pressing finger keys in response to lights and saying words in response to tones.

Gospel according to Mathew (Chapter 6, Verse 24, *Revised Standard Version*), it was proclaimed that "No man can serve two masters; either he will hate the one and love the other, or he will be devoted to the one and despise the other." Yet despite this ancient proclamation, controversy still exists over which stages of processing in one task interfere with those in another (e.g., see Allport, Antonis, & Reynolds, 1972; Broadbent, 1971, 1982; Kahneman, 1973; Keele, 1973; Keele & Neill, 1978; Neisser, 1976; Pashler, 1990, 1993).

1.1 Hypotheses about Interference in Multiple-Task Performance

To illustrate this persistent controversy, we will consider three influential alternative hypotheses about the sources of interference in human multiple-task performance.[3]

Response-selection bottleneck hypothesis. The first of these is the response-selection bottleneck hypothesis, which was proposed originally by Welford (1952, 1959, 1967) and has been championed more recently by some other investigators (e.g., McCann & Johnston, 1992; Pashler, 1984, 1989, 1990, 1993; Pashler & Johnston, 1989).[4] According to it, the perceptual processes for two concurrent tasks may proceed in parallel, allowing the stimuli associated with them to be identified simultaneously. However, there is assumed to be a subsequent process wherein the response for each task is selected separately, and the response selection can be done for only one task at a time, creating an inherent immutable bottleneck in the flow of information from stimulus to response. Thus, if one task comes first and has higher priority, then the response for it would be selected initially, and the selection of another response for a second task would have to wait temporarily, thereby delaying the second task's ultimate completion.[5]

Movement-initiation bottleneck hypothesis. In contrast, an alternative possibility is the movement-initiation bottleneck hypothesis, which has been proposed by Keele (1973; Keele & Neill, 1978; also, for closely related views, see Kantowitz, 1974; Logan & Burkell, 1986; Reynolds, 1964). According to this hypothesis, both perception and response selection may progress in parallel and be completed without mutual interference for two concurrent tasks. However, there is assumed to be a subsequent process that initiates movements separately for

[3] Of course, the hypotheses that we consider here do not constitute an exhaustive set. Many investigators have introduced other accounts of multiple-task performance (e.g., McCleod, 1978; Navon & Gopher, 1979; Norman & Shallice, 1986; Schneider & Detweiler, 1988; Shallice, 1972; Wickens, 1980, 1984; for a comprehensive review, see Gopher & Donchin, 1986). Nevertheless, for present purposes, we have chosen to focus mainly on the three representative cases outlined above, due to their extreme prominence in past literature.

[4] On occasion, Welford's original proposal has also been termed the "single-channel hypothesis." In its earliest form (Welford, 1952), this hypothesis assumed that during the performance of a high-priority first task, people postpone not only response selection but also the perceptual identification of stimuli for a lower-priority second task. Subsequently, however, Welford (1967) placed the bottleneck strictly in the response-selection stage, and acknowledged the possibility that perceptual identification might proceed in parallel for two concurrent tasks. We, like other recent investigators (e.g., Pashler, 1984, 1989, 1990, 1993), therefore prefer the term "response-selection bottleneck hypothesis."

[5] By "response selection" we mean a process through which the categorical identity of a desired response is determined on the basis of a perceptually identified stimulus. For example, the desired response's identity might be "press right index finger." As such, response selection presumably precedes subsequent processes of motor programming and movement initiation that translate the identity of the desired response into muscle commands and overt action (Keele, 1968; Meyer et al., 1988a; Rosenbaum, 1980; Sanders, 1980; Sternberg, 1969).

each task, and that can deal with only one task at a time.[6] This would create a bottleneck wherein movement initiation for a higher-priority first task proceeds from start to finish while the initiation of another movement for a lower-priority second task waits temporarily until the first task's response is completed.

Unitary limited-capacity resource hypothesis. Finally, a third possible case is the unitary limited-capacity resource hypothesis proposed by Kahneman (1973; for related views, also see Gottsdanker, 1980; McCleod, 1978; Moray, 1967; Navon & Gopher, 1979). According to this hypothesis, the central processes involved in response selection, movement initiation, and so forth are not necessarily restricted to dealing with only one task at a time. Instead, it is assumed here that people have a single finite reservoir of processing capacity, which may be allocated flexibly and equitably among various activities, depending on prevailing levels of physiological arousal and task demands. Supposedly this could slow some processes during the performance of multiple concurrent tasks, but it would potentially let them all proceed without any one having to halt along the way.[7]

1.2 Current State of Affairs

Although big differences exist between assumptions made under each of the preceding three hypotheses, previous empirical tests of them have been inconclusive and contradictory. Sometimes one of the bottleneck hypotheses has seemed to prevail, whereas other evidence has favored the unitary limited-capacity resource hypothesis. Consequently, researchers are still arguing back and forth about the sources of interference in multiple-task performance (e.g., see Allport et al., 1972; Broadbent, 1982; McCleod, 1977, 1978; Navon, 1984; Neisser, 1976; Pashler, 1993; McCleod & Posner, 1984).

In our opinion, this persistent conflict stems from two basic problems. First, more consideration needs to be given to the content and strategic consequences of specific instructions that people receive in particular multiple-task situations (for similar viewpoints, see Greenwald & Shulman, 1973; McCleod, 1978; Sanders, 1964). Second, more precise computational modeling and quantitative analyses of people's multiple-task performance is needed to determine where the loci of interference between tasks really are (for similar viewpoints, see Broadbent, 1993; Allport, 1993). We believe that through such a formal approach, much prevailing theoretical controversy would ultimately diminish, and in certain respects, human information processing might be found to exhibit even more flexible capacity than most investigators have assumed thus far. Although this outcome would not suprise everyone (e.g., Neisser, 1976), it could significantly alter the course of future theoretical developments concerning various types of multiple-task performance and the nature of the human information-processing system.

[6] In particular, the movement-initiation process may entail the specification of movement features (e.g., the effector, direction, and extent of movement; Rosenbaum, 1980) and the execution of muscle commands (Keele, 1968; Meyer et al., 1988a, 1990) that mediate overt action.

[7] In addition, Kahneman (1973) also acknowledged the existence of peripheral *structural interference* that arises when two concurrent tasks require simultaneous, mutually-exclusive access to the same physical sense organs or movement effectors. As he noted, structural interference from a high-priority first task could temporarily preclude progress on a lower-priority second task. For example, this might happen when the first task requires making a leftward glance with the eyes whereas the second task requires making a rightward glance, because the eyes cannot simultaneously fixate on two disparate spatial locations. Nevertheless, it was Kahneman's (1973) belief that central processing capacity could be allocated in a graded fashion, thereby letting progress on multiple tasks occur in parallel during various information-processing operations.

Our proposed approach could likewise have important practical benefits in the domains of mental-workload measurement and human-factors engineering. Through computational modeling and precise quantitative analyses of multiple-task performance, problems associated with current measures of mental workload (Moray, 1979; O'Donnell & Eggemeier, 1986) might be solved, and new principles of efficient economical machine-interface design might be formulated (cf. Card, Moran, & Newell, 1983; John, 1990; Kieras & Meyer, 1992).

2. The PRP Procedure

To show that our beliefs have merit, and to explore where they may lead, we focus for now on people's performance in one basic experimental paradigm, the *psychological refractory* period (PRP) procedure, which was evolved originally by Craik (1948), Vince (1948, 1949), Welford (1952), and their colleagues.[8] Several considerations have led us to the present focus. In particular, the PRP procedure embodies one of the simplest and most basic cases of multiple-task performance, making it both a powerful laboratory tool and a useful prototype of some important real-world situations. Results from the PRP procedure are therefore especially relevant to the alternative hypotheses outlined previously. Also, this procedure and its results are amenable to computational modeling whereby such alternatives can be precisely tested.[9]

As Figure 1 shows, the PRP procedure involves a series of discrete test trials. At the start of each trial, there is a brief warning signal, followed by a stimulus for the first of two tasks. In response to it, a subject must react quickly and accurately. Meanwhile, concurrent with or shortly after the Task 1 stimulus, there is another stimulus for a second task. The time between the two stimuli is the *stimulus-onset asynchrony* (SOA), which typically ranges between zero and about 1 sec. In response to the second stimulus, the subject must again react quickly and accurately. However, instructions for typical PRP studies state that the first task should have higher priority, and they may also encourage the subject to make the Task 1 response before the Task 2 response. For example, in a study by Pashler (1984, Experiment 1), "*the subject was instructed to respond as quickly as possible to both tasks in the two-task blocks, with the restriction that the first stimulus must be responded to before the second*" (p. 365). Similarly, in a study by Pashler and Johnston (1989), subjects were told that they "*should respond as rapidly as possible to the first stimulus*," and "*the experimenter emphasized the importance of making the first response as promptly as possible*." Under such instructions, reaction times (RTs) are then measured to determine how much interference actually occurs between Tasks 1 and 2.

[8] The PRP procedure has also been called the *overlapping-tasks procedure* (McCann & Johnston, 1992). Excellent comprehensive reviews of the psychological literature regarding it may be found in Bertelson (1966), Kantowitz (1974), Pashler (1990), Smith (1967), and Welford (1967).

[9] In focusing on the PRP procedure, we do not mean to imply that the present approach and theoretical ideas apply only to this particular case of human multiple-task performance. Rather, our objective is to make progress toward a general, rigorous framework based on which the performance of multiple tasks may be modeled precisely and veridically under a variety of circumstances, ranging from simple combinations of laboratory tasks as in the PRP procedure through much more complex realistic ones such as cockpit operation, air traffic control, and so forth.

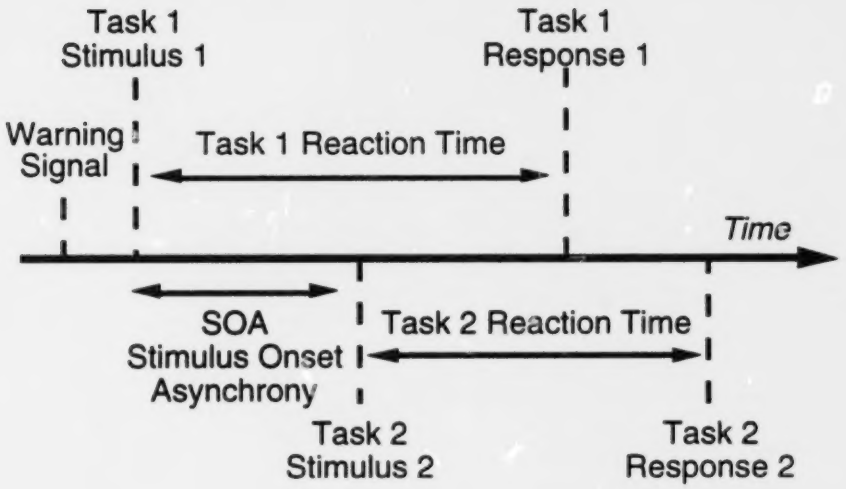

Figure 1. Outline of the events that occur on each trial of the psychological refractory-period (PRP) procedure.

In what follows, we discuss several studies with the PRP procedure. Next we consider the putative implications that these studies have for alternative hypotheses about human multiple-task performance. Then we show how detailed computational modeling of results from the PRP procedure can further clarify the nature of this performance. Results from four representative studies will be considered here. These include ones reported by Hawkins et al. (1979), Karlin and Kestenbaum (1968), McCann and Johnston (1992), and Pashler (1990).

2.1 Representative Studies with The PRP Procedure

Pashler's (1990) study. In the study by Pashler (1990, Experiment 2), subjects made manual responses to visual stimuli (Task 1) and vocal responses to auditory stimuli (Task 2). The stimuli for Task 1 were visual letters (A, B, or C) presented one per trial, which required a choice reaction consisting of a button push with either the index, middle, or ring finger, depending on the letter's identity. The stimuli for Task 2 were 300 and 900 Hz tones presented one per trial, requiring a choice reaction consisting of a vocal "high" or "low" response, depending on the pitch of the tone.[10] The SOAs ranged from 100 to 700 msec.

Some results obtained under these conditions appear in Figure 2, which shows mean RTs for each task plotted versus the SOAs. Here the Task 1 RTs (bottom curve) are uniformly low regardless of the SOA. In contrast, the Task 2 RTs (top curve) are higher at the shortest SOA, but they drop as the SOA increases, yielding a *PRP curve* that manifests a refractory period during which the completion of Task 2 is delayed. (More specifically, the elevation of the Task 2 RTs at the shorter SOAs has sometimes been termed the *PRP effect*.).

[10] As we discuss later, this study (Pashler, 1990, Experiment 2) also included other conditions in which Task 1 involved auditory stimuli and vocal responses, whereas Task 2 involved visual stimuli and manual responses.

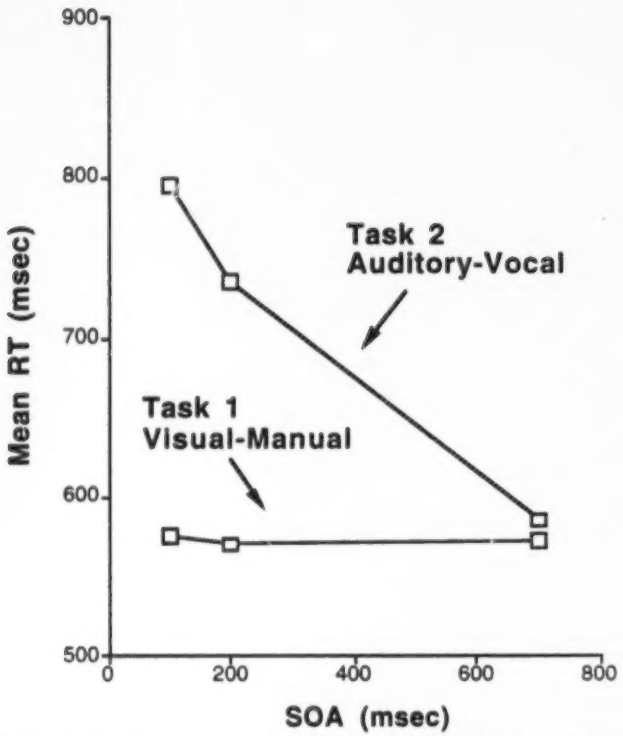

Figure 2. Results from a typical experiment with the PRP procedure (Pashler, 1990, Exp. 2).

Given these and other related results, Pashler (1984, 1989, 1990, 1993) -- like Welford (1967) and Smith (1967) before him -- has championed the response-selection bottleneck hypothesis. For example, he argued that this hypothesis best explains why PRP effects occur even when Task 2 involves stimuli and responses whose modalities differ from those of Task 1. This is because the two tasks still require response selection regardless of their modalities, so when a Task 1 stimulus enters the selection bottleneck, it would necessarily delay progress on Task 2. A bottleneck that lets Task 1 through immediately would likewise account for why Task 1 RTs are uniformly low regardless of the SOA.

McCann and Johnston's (1992) study. Some other putative evidence for the response-selection bottleneck hypothesis comes from a study by McCann and Johnston (1992, Experiment 1) with the PRP procedure. Here Task 1 involved vocal responses to auditory stimuli, and Task 2 involved manual responses to visual stimuli. The mappings between the Task 2 stimuli and responses were either compatible or incompatible. S-R compatibility was manipulated by presenting Task 2 stimuli whose shapes and sizes both varied during each trial block. For example, on some trials, a small, medium, or large triangle that involved a compatible S-R mapping was presented. In response to it, subjects respectively pressed a key with either the ring, middle, or index finger of one (e.g., left) hand. A simple correspondence existed between stimulus size and spatial finger position (e.g., small --> ring, medium --> middle, and large --> index). On other trials, a small, medium, or large rectangle that involved an incompatible S-R mapping was presented. In response to it, subjects pressed either the ring, middle, or index finger of the other (e.g., right) hand, but the relationship between stimulus size and spatial finger position was more complex.

Figure 3 shows results that McCann and Johnston (1992) obtained through this procedure. A large S-R compatibility effect occurred in Task 2 RTs (top pair of PRP curves), with manual responses being slower under the incompatible mapping than under the compatible mapping. The compatibility effect was roughly additive with the effect of SOA, making the PRP curves be nearly parallel. Yet the Task 1 RTs were relatively low regardless of the SOA. Consequently, consistent with Welford's (1952, 1959, 1967) and Pashler's (1984, 1989, 1990, 1993) conclusions, McCann and Johnston inferred there is a response-selection bottleneck through which performance of Task 1 passes first, temporarily blocking the completion of Task 2.

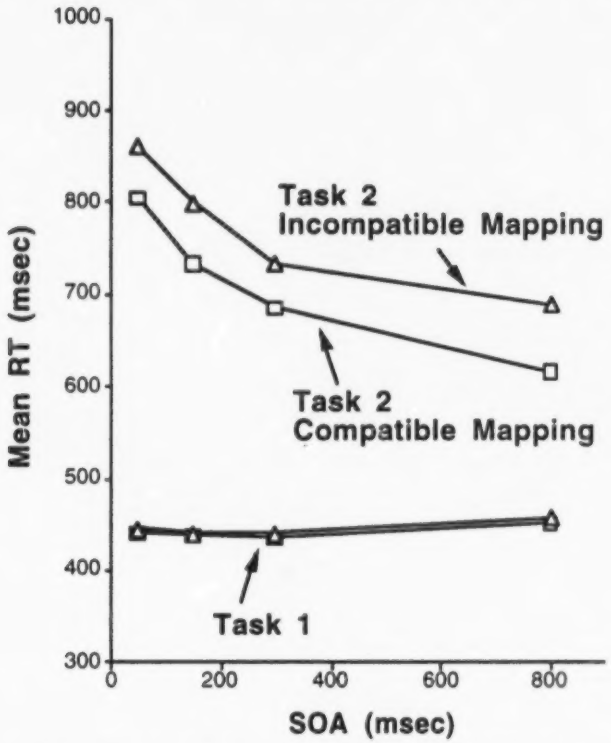

Figure 3. Results obtained by McCann and Johnston (1992, Exp. 1) from a study of stimulus-response compatibility effects in the PRP procedure.

This inference is based on a rationale that McCann and Johnston (1992) call the *locus-of-slack approach*. Its logic appears in Figure 4. Here we have shown how the S-R compatibility in Task 2 should affect RTs if there is a response-selection bottleneck. At the top of the figure, the processes for Task 1 are assumed to proceed immediately from start to finish. Also, after a short SOA, the perceptual stage of Task 2 is completed in parallel with Task 1. Then, because of the assumed response-selection bottleneck, progress on Task 2 halts, creating a period of temporal "slack" or "deadtime" in Task 2 (Figure 4, dotted intervals) until the response for Task 1 has been selected. When response selection later resumes for Task 2, it presumably takes less time with a compatible S-R mapping than with an incompatible mapping, yielding a difference in mean Task 2 RTs. Furthermore, this compatibility effect should be the same regardless of the SOA, because increasing the SOA reduces the intermediate slack during Task 2, but since response selection in Task 2 always occurs after the slack, contributions from

the different response-selection times still remain, just as McCann and Johnston (1992) found."

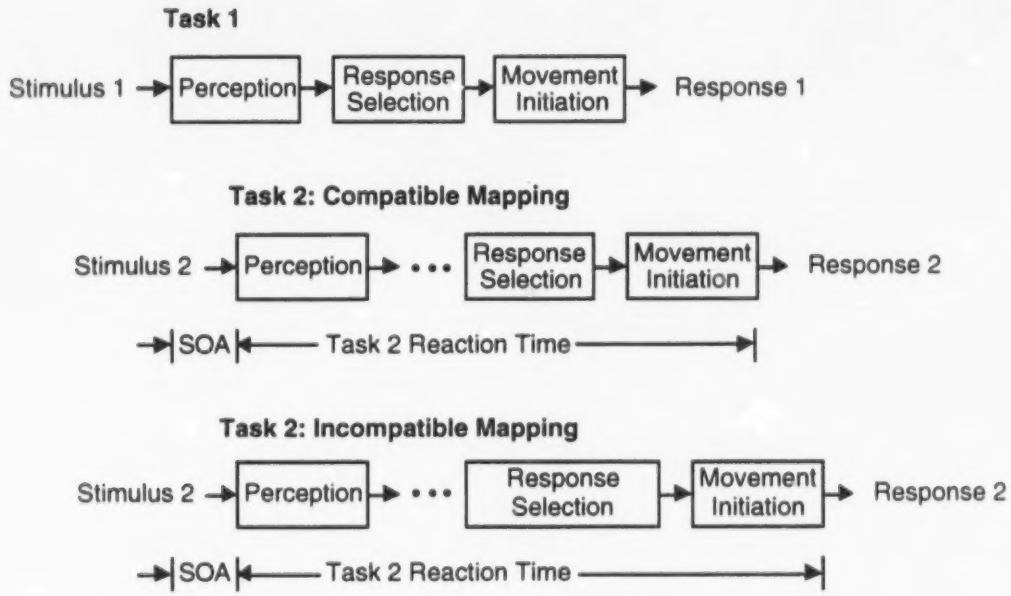

Figure 4. A processing-stage model that accounts for the results of McCann and Johnston (1992, Exp. 4) based on the locus-of-slack approach and the response-selection bottleneck hypothesis. For further details, see text and Figure 3.

Karlin and Kestenbaum's (1968) study. It is not always the case, however, that empirical evidence supports the hypothesis of a bottleneck in response selection. On at least some occasions, there has appeared instead to be a bottleneck at a later stage of processing, perhaps associated with movement initiation. For example, one such occasion may be found in a study by Karlin and Kestenbaum (1968) with the PRP procedure.

Here Task 1 involved manual choice reactions (left-hand finger presses) to visual stimuli (digits), and Task 2 involved manual simple or choice reactions (right-hand finger presses) to auditory stimuli (tones). In the simple-reaction case, there was only one possible stimulus and response during Task 2, whereas in the choice-reaction case, there were two possible stimuli and two responses. This difference between the simple and choice reactions might be expected to affect response selection in Task 2 regardless of the SOA, much as S-R compatibility does (Sanders, 1980; Sternberg, 1969), yielding parallel PRP curves like McCann and Johnston (1992) found. To be specific, response selection should take longer for the choice-reaction case than for the simple-reaction case of Task 2 whether the SOA is short or long, because the choice

[11] The locus-of-slack approach has also been taken earlier in work by several other investigators (e.g., Karlin & Kestenbaum 1968; Keele, 1973; Keele & Neill, 1978; Logan & Burkell, 1986; Pashler, 1984, 1993; Pashler & Johnston, 1989; Schvaneveldt, 1969; Schweickert, 1980). In essence, their work embodies a special case of Sternberg's (1969) well-known additive-factor method. The delay of Task 2 responses induced by the SOA factor constitutes an effect on one stage of "processing" during Task 2 (i.e., the wait for Task 1 to be completed), and the subsequent delay of Task 2 responses caused by variations of other Task 2 factors like S-R compatibility constitutes an effect on a later processing stage (e.g., Task 2 response selection).

reactions require response selection based on the identities of the stimuli, whereas simple reactions do not. In the simple-reaction case, it might also be possible to foreshorten the processes of motor programming and movement initiation regardless of the SOA (Sanders, 1980; Sternberg, 1969; Sternberg, Monsell, Knoll, & Wright, 1978).

Nevertheless, Karlin and Kestenbaum's (1968) study manifested a huge interaction between the effects of SOA and the number of stimulus-response pairs that subjects had to deal with during Task 2. Figure 5 shows the form of the obtained results. At the shortest SOA, the Task 2 RTs are about equally high regardless of whether they involved simple or choice reactions, but at the longer SOAs, the RTs of the simple reactions are much lower than those of the choice reactions, yielding strongly divergent PRP curves. Even so, the Task 1 RTs remained relatively constant regardless of the SOA and the type of Task 2 that was involved.

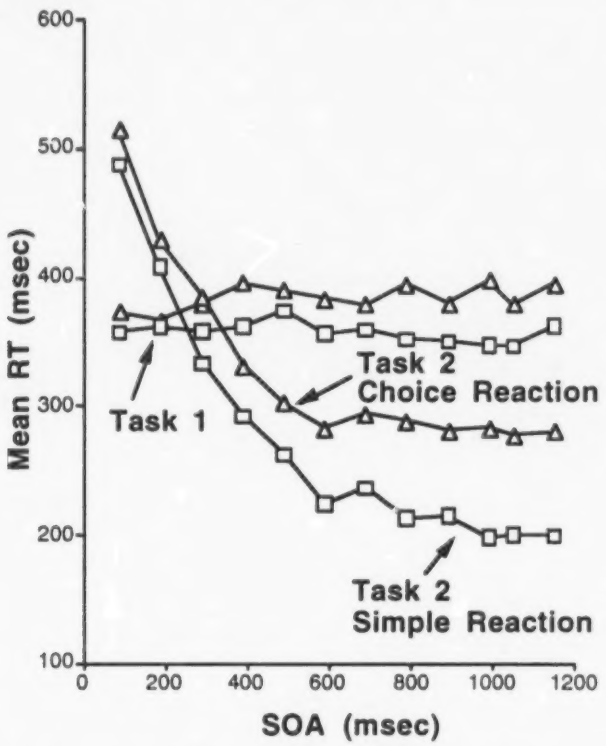

Figure 5. Results obtained by Karlin and Kestenbaum (1968) from a study of "simple" versus "choice" reactions in the PRP procedure.

As Keele (1973; Keele & Neill, 1978) has argued, this outcome seems more consistent with a bottleneck in movement initiation rather than response selection. Figure 6 illustrates why. Here we have shown what the RTs should look like if response selection proceeds simultaneously for Task 1 and Task 2, but a movement-initiation bottleneck occurs before the output of overt Task 2 responses at short SOAs. Because of reasons mentioned previously, response selection would presumably take less time during Task 2 when it involves simple reactions rather than choice reactions. Also, with a movement-initiation bottleneck, some temporal slack (deadtime) in the progress of Task 2 would follow a short SOA. As a result, however, the slack would come immediately before movement initiation, not before response selection (cf. Figure 4). Consequently, the longer response-selection process for choice

reactions in Task 2 would have enough time to finish without changing when the subsequent movement initiation starts.[12] In turn, this would yield equal Task 2 RTs for choice and simple reactions. Furthermore, as the SOA increases, the temporal slack before movement initiation in Task 2 would diminish, and a difference between Task 2 simple versus choice RTs would then emerge, just as Karlin and Kestenbaum (1968) found.

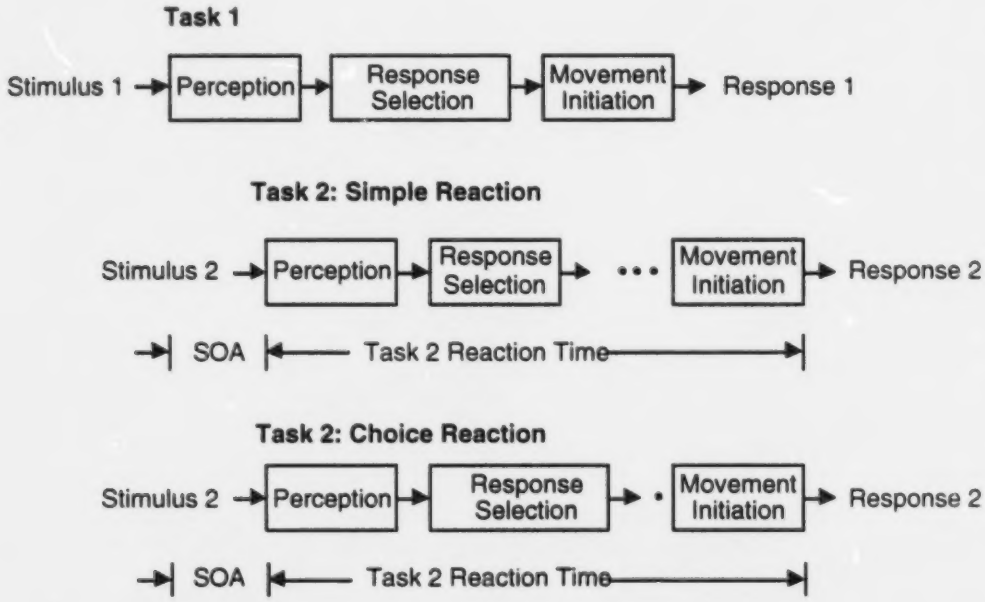

Figure 6. A processing-stage model that accounts for the results of Karlin and Kestenbaum (1968) based on the locus-of-slack approach and the movement-initiation bottleneck hypothesis. For further details, see text and Figure 5.

Hawkins et al.'s (1979) study. Some more evidence suggesting a bottleneck in movement initiation rather than response selection has been reported by Hawkins, Rodriguez, and Reicher (1979). They conducted a study with the PRP procedure wherein Task 1 required choice reactions involving manual responses (left-hand finger presses) to auditory stimuli (tones) and Task 2 required choice reactions involving manual responses (right-hand finger presses) to visual stimuli (digits). The response-selection process for Task 2 was varied by having subjects deal with either two or eight stimulus-response pairs during Task 2 (cf. Sanders, 1980; Sternberg, 1969). When Task 2 involved two S-R pairs, the alternative stimuli were the digits 2 and 3, and the alternative responses were key presses with the right-hand index and middle fingers, respectively. When Task 2 involved eight S-R pairs, the alternative stimuli were the digits 2 through 9; for four of these digits (2, 5, 6, and 9), subjects responded by pressing the right-hand index finger key, and for the other four digits (3, 4, 7, and 8), they responded by pressing the right-hand middle finger key.

[12] Using the terminology of PERT charts, which provide a pictorial representation of constraints on the temporal order among various processes, one would say here that at a short SOA, the response-selection process for Task 2 does not lie on the "critical path" whose length determines the Task 2 RT (John, 1990; Schweickert, 1980; Schweickert & Boggs, 1984).

Figure 7 shows the results that this variation produced. When the SOA was long, the Task 2 RTs depended substantially on the number of S-R pairs in Task 2; the condition with eight S-R pairs yielded slower responses than did the condition with two S-R pairs. At shorter SOAs, however, the number of S-R pairs had virtually no effect on the Task 2 RTs, as shown by the convergence of the PRP curves in the upper left corner of Figure 7. Again, as in Figure 5, such a pattern suggests a bottleneck in movement initiation rather than response selection, because the difficulty of selecting responses in Task 2 (i.e., the S-R numerosity effect) was presumably masked by post-selection temporal slack.

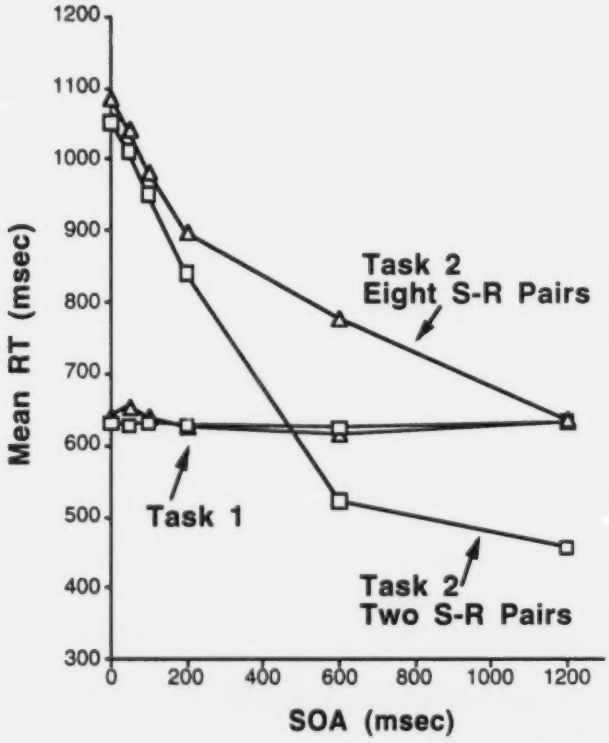

Figure 7. Results obtained by Hawkins et al. (1979) from a study of stimulus-response numerosity effects in the PRP procedure.

Alternatively, one might argue that S-R numerosity affects stimulus identification rather than response selection. If so, then the results of Hawkins et al. (1979) would be consistent with the response-selection bottleneck hypothesis (Figure 4). However, this possibility seems extremely implausible. Sternberg (1969) has shown that the effects of S-R numerosity and S-R compatibility on RT interact, suggesting that at least part of the numerosity effect occurs during response selection. Furthermore, an extensive review of representative studies in the literature has revealed that most, if not all, of the numerosity effect occurs during response selection (Sanders, 1980). In contrast, for the response-selection bottleneck hypothesis to explain the results of Hawkins et al. (1979), less than 20% of the numerosity effect would have had to occur during response selection.

Pashler's (1990) study revisited. Finally, to complete the present picture, let us return briefly to the study by Pashler (1990, Experiment 2), which was mentioned previously. Here subjects performed a visual-manual choice-reaction task along with an auditory-vocal choice-

reaction task. During some trial blocks, the order in which the stimuli occurred on each trial was constant, so subjects knew beforehand which task would come first, as under the typical PRP procedure (Figure 1). During other trial blocks, the stimulus order on each trial was varied randomly, so subjects did not know which task would come first. However, under both the variable-order and constant-order conditions, the subjects' instructions were to "respond as promptly as possible to the *first* stimulus that appears, and then respond as promptly as possible to the second stimulus" (Pashler, 1990, p. 831).

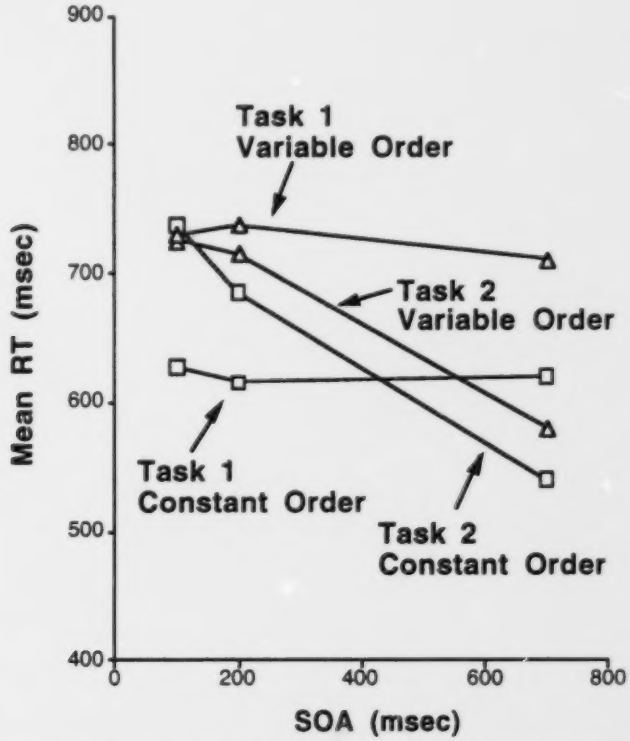

Figure 8. Results obtained by Pashler (1990, Exp. 2) from a study in which, during each block of trials with the PRP procedure, the order of the Task 1 and Task 2 stimuli was either constant or variable, and correspondingly, subjects were either certain or uncertain about what the stimulus order would be.

Figure 8 shows what happened on trials when the auditory-vocal task came first and the visual-manual task was second in Pashler's (1990, Exp. 2) study. The Task 1 RTs were substantially (at least 100 msec) higher in the variable-order condition (filled triangles; Task 1 not known beforehand) than in the constant-order condition (filled squares; Task 1 known beforehand). In contrast, the Task 2 RTs were much less affected by the variable-order and constant-order conditions. Indeed, at the shortest (100 msec) SOA, Task 2 responses took slightly less time when the stimulus order was variable across trials than when it was constant! Also, as the SOA increased, the Task 2 RTdecreased at about the same rate in both the variable-order and constant-order conditions, yielding rather similar PRP curves that never differed from each other by more than about 30 msec. The same qualitative pattern of results likewise

occurred when the visual-manual task came first and the auditory-vocal task was second.[13]

This outcome casts doubt on both the response-selection and movement-initiation bottleneck hypotheses. They each predict that when the completion of Task 1 is slowed by cognitive factors such as subjects' uncertainty about stimulus order, then the slowing should propagate onward in commensurate fashion to delay the completion of Task 2.[14] However, additional Task 2 delays (i.e., increases of Task 2 RTs) did not occur during Pashler's (1990, Experiment 2) study when uncertainties about stimulus and task order were introduced, even though these uncertainties substantially slowed Task 1 completion.

Pashler's (1990, Experiment 2) data may instead be interpreted as manifesting a parallel processing system that gracefully adapts to complex task contingencies without undue debilitation. Of course, this is remindful of what Kahneman (1973) proposed under his unitary limited-capacity resource hypothesis. Yet the ultimate merits of the latter hypothesis are difficult to assess because it was never stated quantitatively, and meanwhile the conflicting results from other studies with the PRP procedure (e.g., Hawkins et al., 1979; Karlin & Kestenbaum, 1968; McCann & Johnston, 1992) leave the nature of human multiple-task performance shrouded in mystery.

2.2 Theoretical Implications

In light of considerations such as the preceding ones, no extant theory of human multiple-task performance can account thoroughly and veridically for the rich body of data obtained from the PRP procedure and other related paradigms (for a similar assessment, see McCleod, 1978). Although potentially quantifiable, the response-selection bottleneck hypothesis (Welford, 1952, 1959, 1967) and the movement-initiation bottleneck hypothesis (Keele, 1973; Keele & Neill, 1978) are not flexible enough to deal with the various patterns of factor effects caused by changes in S-R compatibility (McCann & Johnston, 1992), number of S-R pairs (Hawkins et al., 1979; Karlin & Kestenbaum, 1968), uncertainty about stimulus order (Pashler, 1990), and so forth. The unitary limited-capacity resource hypothesis (Kahneman, 1973) and its many descendants (e.g., McCleod, 1978; Navon & Gopher, 1979; Norman & Shallice, 1986; Schneider & Detweiler, 1988; Wickens, 1980, 1984) provide more of the needed flexibility, but they remain essentially qualitative in nature, and they do not make precise quantitative predictions whereby one may rigorously test them.[15]

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[13] The only exception to this generalization was that at the longest SOA, RTs for the auditory-vocal second task were somewhat higher in the variable-order condition than in the constant-order condition. Even so, however, at the shortest SOA, this task yielded RTs that were again a bit less in the variable-order condition than in the constant-order condition.

[14] The basis of this prediction is straightforward. According to the response-selection bottleneck hypothesis, for example, selection and execution of a Task 2 response may not begin until the Task 1 response has been selected. Delaying the completion of Task 1 response selection (e.g., by making the stimulus order be uncertain) should therefore increase the Task 2 RTs as well.

[15] In addition to the above hypotheses and theories, models that have been developed by human-factors engineers to assess mental workload in practical situations are relevant for characterizing multiple-task performance (e.g., Chubb, 1981; Harris et al., 1987; John, 1990). However, they too have serious limitations. For example, they fail to provide a sufficiently detailed conceptual analysis of the basic perceptual, cognitive, and motor processes that mediate the speed, accuracy, and flexibility of such performance.

The present report is therefore intended to take steps toward rectifying this prevailing problematic situation. In what follows, we introduce a new, more precise, powerful theoretical framework for characterizing human multiple-task performance. Next, on the basis of our framework, we show how detailed executable computational models of such performance may be developed. Then we apply these models to account quantitatively for the results obtained from a variety of studies with the PRP procedure. Some major conclusions from this application are that: (1) The slowing of Task 2 responses in the PRP procedure does not necessarily imply a central bottleneck in response selection; instead, response selection and other central cognitive processes may proceed simultaneously for multiple tasks without much, if any, interference. (2) The coordination of performance for tasks in the PRP procedure and in other multiple-task situations may be mediated by a flexible executive process programmed to implement optimal strategies consistent with task instructions and peripheral perceptual-motor limitations. (3) The between-task interference typically observed in the PRP procedure and other multiple-task situations may be attributable mostly, perhaps even entirely, to peripheral perceptual-motor limitations and to people's strategies for obeying specific task instructions.

3. A Framework for Computational Modeling of Multiple-Task Performance

Our theoretical framework is based on five overarching principles (Kieras & Meyer, 1994). First, we require that our computational models of multiple-task performance be built within *a fixed detailed comprehensive architecture* for the human information-processing system. In this respect, our efforts extend those of some previous theorists who have likewise advocated the development of architecturally consistent computational models (e.g., Anderson, 1976, 1983; Card, Moran, & Newell, 1983; Laird, Newell, & Rosenbloom, 1987; Newell, 1990). Secondly, again like them and others (e.g., Hunt & Lansman, 1986; Townsend, 1986), we use *a production-system formalism* for the simulation programs that instantiate our models. Thirdly, unlike the models developed by some other theorists, ours have *no inherent central-processing bottleneck*. Instead, applying a fourth principle, we as much as possible *attribute apparent decrements in multiple-task performance to task instructions* that bias people toward exhibiting less than their full capacity. Also, applying a fifth principle, we try to *take complete account of peripheral perceptual-motor constraints* on task coordination. As a result, a clearer picture of the ways in which people actually perform multiple concurrent tasks may emerge.

3.1 The EPIC Architecture

An overview of the architecture used to build our models appears in Figure 9 (also see Kieras & Meyer, 1994). We call this the *Executive Process, Interactive Control (EPIC) Architecture*. It has a variety of system components that, in combination, may mediate a broad range of human perceptual-motor and cognitive skills. For example, EPIC includes visual, auditory, and tactile *perceptual processors* that receive inputs from simulated *physical sensors*. They send outputs to a central *working memory* that is used by a *cognitive processor* to perform various tasks. Through a *production-rule interpreter* in the cognitive processor, responses are selected and sent to *vocal and manual motor processors*, which prepare and initiate movements by simulated *physical effectors*. Also, there is an *ocular motor processor* for moving the eyes, whose spatial position determines what inputs enter the visual perceptual processor.

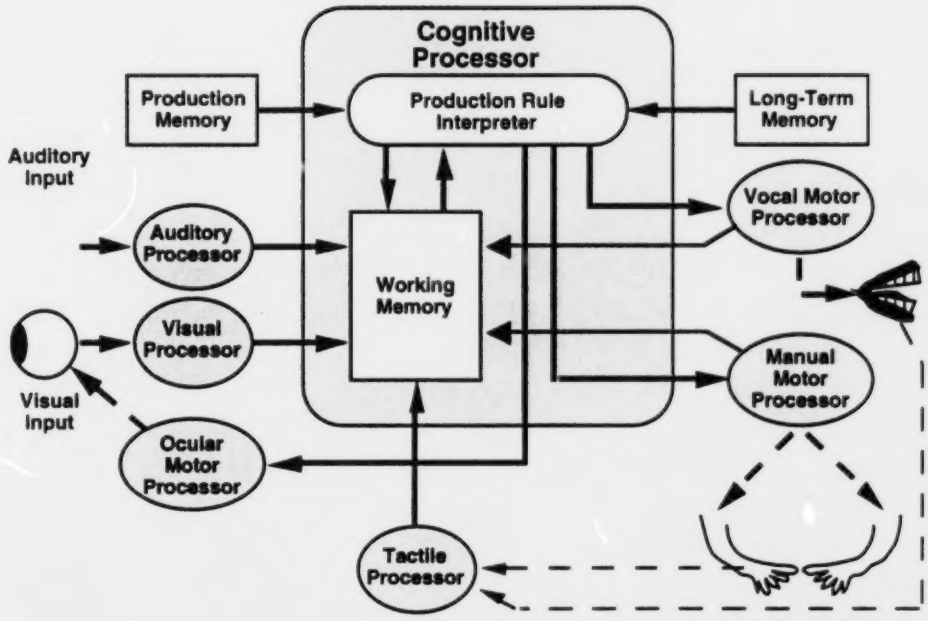

Figure 9. Overview of the information-processing components associated with the Executive-Process/Interactive-Control (EPIC) architecture for formulating computational models of human multiple-task performance.

For each of these complementary system components, we make assumptions about the symbolic representations, input/output transformations, and temporal delays that they entail. Our assumptions are guided by a desire to keep EPIC reasonably simple and precise but consistent with available empirical data about the nature of human information-processing (e.g., Atkinson, Hernstein, Lindzey, & Luce, 1988; Boff, Kaufman, & Thomas, 1986; Meyer & Kornblum, 1993). In the following subsections, the assumed properties of EPIC's perceptual processors, cognitive processor, working memory, and motor processors will be outlined more fully. Also, a summary of these properties appears in Table 1.

3.2 Assumptions About The Perceptual Processors

Stimulus detection and identification. Regarding EPIC's perceptual processors, we assume that the inputs to them are meaningful physical stimuli (i.e., categorizable objects and events) received through particular sensory modalities (e.g., vision, audition, and touch). When a stimulus is presented (e.g., via a simulated display device), a corresponding perceptual processor sends symbols to working memory, indicating that the stimulus has been detected (e.g., `AUDITORY DETECTION ONSET`) and specifying what its identity is (e.g., `AUDITORY TONE 800 ON`). This transmission is assumed to take time and to occur asynchronously, in parallel, with operations by EPIC's cognitive processor, motor processors, and other perceptual processors.[16]

[16] At present, the transformations performed by EPIC's perceptual processors, which convert sensory stimulus inputs into detection and identification symbols, are achieved through simple table-lookup operations. We do not attempt to implement complex pattern-recognition algorithms, because this is not necessary for our purposes.

Table 1

Assumptions about EPIC's System Components

Type of Component	*Assumed Properties*
perceptual processors	asynchronous operation, in parallel with cognitive processor detection and identification symbols transmitted to working memory transmission times depend on modality, intensity, and discriminability
motor processors	response symbols received as inputs movement features generated for physical outputs feature generation done serially with set time increments anticipatory feature generation used for response preparation movement initiation done after feature generation completed efference copies of motoric representations sent to working memory
cognitive processor	programmed with production rules (`IF CONDITION, THEN ACTION`) rules interpreted by Parsimonious Production System conditions consist of goals, step tags, and notes step tags in conditions govern flow of control complex conflict-resolution criteria and spreading activation not used actions regulate working memory and perceptual/motor processors cyclical operation with set mean cycle duration no limit on number of simultaneous rule tests and firings no inherent central-processing bottleneck
working memory	contents include goals, step tags, and notes contents managed and used by cognitive processor capacity and duration sufficient for PRP performance

Perceptual transmission times. In our models of multiple-task performance, numerical parameter values are assigned to the times taken by each of the perceptual processors for transmitting the stimulus detection and identification symbols to working memory. Under typical circumstances, the stimulus-detection times would be relatively fast and depend on factors such as stimulus intensity and the sensory modalities involved, consistent with RTs from standard simple-reaction experiments (e.g., Woodworth & Schlosberg, 1954). On the other hand, consistent with RTs from standard choice-reaction experiments, the stimulus-identification times would be slower, vary as a function of stimulus discriminability, and perhaps exhibit a different pattern of modality effects than stimulus detection does. As discussed more fully later, we determine the exact values of these parameters on the basis of either representative measurements reported in past literature or estimates obtained from whatever data set is being modeled at the moment.

3.3 Assumptions About The Motor Processors

Response symbols and movement features. Regarding EPIC's motor processors, we assume that the inputs to them are symbols for the identities of responses (e.g., `LEFT-INDEX`) selected by the cognitive processor. The response symbols get converted by the motor processors to output commands that control simulated physical effectors. Following past studies of manual, vocal, and ocular motor programming (e.g., Abrams & Jonides, 1988; Meyer & Gordon, 1985; Rosenbaum, 1980), this conversion is further assumed to involve generating movement features appropriate to the intended response modality. For example, the movement features would include specifications of the hand and finger (e.g., `LEFT, INDEX`) to be used in a manual key press, or specifications of the place and manner of articulation (e.g., `LABIAL, STOP`) to be used in the initial consonant of a vocal syllable.

Serial feature generation. Likewise consistent with results of past research on motor programming, movement features are generated serially under EPIC, with the generation of each required feature taking an additional time increment whose value constitutes a prespecified parameter of our models. Depending on prior input from the cognitive processor, each motor processor may program some movement features in advance, thus reducing ultimate reaction times (Coles et al., 1985; Miller, 1982; Osman et al., 1992; Rosenbaum & Kornblum, 1982). Then, after feature generation has been completed, a subsequent initiation operation by the currently relevant motor processor starts overt movement. Also, along the way, the motor processors send efference copies of their inputs and outputs back to working memory for the cognitive processor's use, as suggested by studies of response monitoring and error correction (e.g., Gehring, Goss, Coles, Meyer, & Donchin, 1993; von Holst & Mittelstaedt; 1950).

Single manual motor processor. As indicated already, our current version of EPIC has a single manual motor processor that is responsible for producing movements with both the right and left hands; there is no separate independent controller for each hand. Because manual responses are assumed to be programmed in terms of features such as the hand and finger to be used in a movement, this may then yield increased interference between one concurrent task and another when they require responses with different hands rather than different modalities (e.g., manual and vocal), even though the two hands themselves are physically distinct. Such increased interference has been observed by some experimenters (e.g., McCleod, 1977; Pashler, 1990) in multiple-task situations, supporting our current motor-processor assumptions.

3.4 Assumptions About The Cognitive Processor

Production-rule programming. Regarding EPIC's cognitive processor, we assume that it is programmed with production rules that are stored in a production-rule memory. As in other related models (e.g., Anderson, 1976, 1983; Hunt & Lansman, 1986; Laird, Newell, & Rosenbloom, 1987), the present production rules have the form `IF CONDITION, THEN ACTION`. To ensure that the rules' conditions and actions are simple and easily understood, we represent them using the *Parsimonius Production System* (*PPS*) of Kieras and colleagues (Bovair, Kieras, & Polson, 1990; Covrigaru & Kieras, 1987).

Representation of rule conditions. The conditions for our production rules consist of information about *goals*, *step tags*, and *notes* stored in EPIC's working memory. Goals are represented with symbols (e.g., `GOAL DO TASK 1`) that enable the performance of particular tasks. Step tags are represented with symbols (e.g., `STEP DO CHECK FOR ALPHA`) that provide sequential control over exactly when a rule may have its actions executed during the course of information processing. Notes are represented with symbols that keep track of inputs and outputs related to activities by the perceptual processors, cognitive processor, and motor processors. Included among the notes may be ones that serve as trial-status and task-status indicators (e.g., `TRIAL UNDERWAY; TASK 1 DONE`), stimulus and response identification symbols (e.g., `AUDITORY TONE 800 ON; RESPONSE IS LEFT-INDEX`), and strategic response-transmission modes (e.g., `STRATEGY TASK 1 IS IMMEDIATE`)

Representation of rule actions. The actions of our production rules modify the contents of working memory and send instructions to EPIC'S perceptual and motor processors. Additions and deletions to working memory's data base are represented with symbols (e.g., `ADDDB (STEP WAIT FOR TASK 1 RESPONSE COMPLETION); DELDB (AUDITORY TONE 800 ON)`) that maintain the current state of the processing system.[17] Instructions to the motor processors are represented with symbols (e.g., `SEND-TO-MOTOR (MANUAL PERFORM LEFT-INDEX)`) that direct their subsequent activities.

Testing of rule conditions and execution of rule actions. Under EPIC, production-rule conditions are tested and production-rule actions are executed through an intepreter based on the Parsimonius Production System developed by Kieras and colleagues (Bovair, Kieras, & Polson, 1990; Covrigaru & Kieras, 1987). If a particular rule has its condition satisfied by the contents of working memory (i.e., the goals, step tags, and notes stored there), then its actions are executed. For example, suppose that in Task 1 of the PRP procedure, the instructions state that a key press with the left-hand index finger should be made immediately in response to an 800 Hz tone. Then during the response-selection process for Task 1, after the onset of this tone, our production-rule interpreter might test the condition and execute the actions of the following rule:

[17] The term "ADDDB" stands for "add item to data base," and the term "DELDB" stands for "delete item from data base." The items to be respectively added or deleted are represented by the parenthesized lists of symbols that follow these terms.

```
IF
 ((GOAL DO TASK 1)
   (STEP DO CHECK FOR ALPHA)
   (AUDITORY TONE 800 ON)
   (STRATEGY TASK 1 IS IMMEDIATE))
THEN
  ((SEND-TO-MOTOR (MANUAL PERFORM LEFT INDEX))
    (ADDDB (TASK 1 RESPONSE UNDERWAY))
    (ADDDB (STEP WAIT FOR TASK 1 RESPONSE COMPLETION))
    (DELDB (STEP DO CHECK FOR ALPHA))
    (DELDB (AUDITORY TONE 800 ON))).
```

Given that the requisite goal, step tag, and notes are already in working memory, this rule would be "fired", causing the symbol for a left index-finger keypress to be selected and sent to the manual motor processor in response to the 800 Hz tone.

Unlike in some other production-system models (e.g., Anderson, 1976, 1983; Hunt & Lansman, 1986; Laird et al., 1987; McDermott & Forgy, 1978), EPIC's production-rule interpreter does not rely on complex conflict-resolution criteria or spreading-activation mechanisms to decide what rules should be fired. Instead, rule firings are controlled solely by the content of the rules' conditions. Whenever all of the conditions associated with a particular rule are satisfied by the current contents of working memory, then all of its actions will be executed, regardless of the status of any other rules. To preclude the execution of simultaneous conflicting actions, the conditions of the rules are defined such that two or more rules can never fire at the same time if their actions conflict.

Cyclical operation and parallel rule firing. Regarding EPIC's cognitive processor, we assume furthermore that it operates cyclically and has a fixed short mean duration (e.g., 50 msec) per cycle, with no pause between the end of one cycle and the beginning of the next. This assumption is consistent with the temporal granularity of perceived stimulus sucessiveness (Kristofferson, 1967), the spectral characteristics of simple RT distributions (Dehaene, 1992, 1993), and the periodicity of EEG brain activity (e.g., alpha rhythms; Callaway & Yeager, 1960; Ray, 1990). At the start of each cognitive-processor cycle, the contents of working memory are updated with new inputs from the perceptual and motor processors. Next, the production-rule interpreter tests the conditions of all rules currently stored in the cognitive processor's production-rule (procedural) memory. Then, for every rule that has its conditions satisfied by the present contents of working memory, the associated actions are executed in parallel at the end of the cycle. The durations of the cognitive processor's cycles do not depend on the number of production rules involved. Unlike in other production-system models, *EPIC imposes no upper limit on how many rules may be tested or "fired" at the same time.*

The latter radical feature means that in EPIC, there is no inherent central-processing bottleneck to impede response selection during the performance of multiple concurrent tasks. Under the regimen of the PRP procedure, for example, our cognitive processor has the potential to select responses simultaneously for both Task 1 and Task 2. Nevertheless, because subjects in the PRP procedure are instructed to produce Task 1 responses sooner and faster than Task 2 responses (*Section 2*), and also because EPIC's perceptual/motor processors are limited, we would still expect some apparent between-task interference (e.g., increases of Task 2 RTs at short SOAs).

3.5 Assumptions About Working Memory

Contents of working memory. As indicated already, we assume that EPIC's working memory contains items relevant to activities by the perceptual processors, cognitive processor, and motor processors. These items may include notes of various sorts (viz., stimulus-detection symbols, stimulus-identification symbols, strategic response-transmission modes, response-identification symbols, and efference copies of motoric representations), step tags (i.e., sequential control information), and goals for different tasks. The cognitive processor presumably maintains and uses this information in various aspects of task performance.

Capacity and durability. For present purposes, we further assume that EPIC's working memory has sufficient capacity and durability to maintain an accurate representation of all the information needed in performing the two tasks of typical studies with the PRP procedure. No mechanisms of information rehearsal, decay, or overflow are included here. Because of the PRP procedure's relative simplicity, this omission seems reasonable at the moment.[18]

3.6 Mechanisms for Coordinating Performance Across Multiple Concurrent Tasks

Within the context of the EPIC architecture, there are numerous ways whereby perceptual-motor and cognitive performance might be coordinated across multiple concurrent tasks. Such coordination could occur through mechanisms that appropriately insert and delete task goals in working memory, direct the eyes to look at one place or another in visual space, send selected response symbols to either motor processors or working memory, and partially prepare the movement features of anticipated responses ahead of time. By using these mechanisms optimally, a person could maximize the performance of two or more distinct tasks, subject to task instructions and limitations of perceptual-motor resources. Specifically, we next discuss how this potential ability applies to human multiple-task performance under the PRP procedure.

4. Application to Multiple-Task Performance Under The PRP Procedure

To apply the EPIC architecture in modeling multiple-task performance under the PRP procedure, our approach entails two steps. First, for each of this procedure's two tasks, we specify a computational process that can perform the task both alone and in combination with other tasks. Second, we specify an executive process that oversees progress on the two tasks and that adheres to the instructions of the PRP procedure while optimally exploiting available system resources. Taken together, the specified executive and task processes constitute explicit theoretical claims that we make here about how people actually do perform in at least some cases under the PRP procedure.

In this regard, the present theoretical claims have a family resemblance to ones introduced previously by some other investigators (e.g., Duncan, 1986; Kahneman, 1973; Logan, 1985; Norman & Shallice, 1986; Shallice, 1972). For example, Norman and Shallice (1986) proposed that multiple-task performance may be mediated by a Supervisory Attentional System (SAS), which regulates interactions among procedural schemata associated with individual perceptual-motor and cognitive tasks. The characteristics attributed to the SAS and the procedural

[18] Of course, our present assumptions about working memory will not suffice more generally. Signficant capacity limits on the verbal articulatory loop, as well as other forms of temporary storage, have already been demonstrated in other multiple-task situations (e.g., see Baddeley, 1986). Thus, the current treatment will have to be modified and elaborated when we extend the EPIC architecture to additional task domains.

schemata are somewhat like those that we embody respectively in our executive and task processes. Nevertheless, how we treat these processes constitutes a significant advance; they are specified more precisely here than in prior cases, and they are implemented as executable computer programs whose outputs yield detailed empirically-testable quantitative predictions, whereas the SAS and other such proposals have amounted to no more than qualitative speculations.

4.1 Specification of Task Processes

Production rules for Task 1 and Task 2. The specified processes for performing the PRP procedure's two tasks are based on modular sets of production rules like those discussed earlier (*Section 3.4*). We start by defining a set of rules that can perform Task 1 with inputs from EPIC's perceptual processors and outputs to its motor processors. A principal function of the Task 1 rule set is response selection, which involves identifying an appropriate response for each Task 1 stimulus and sending it (i.e., the selected response symbol; e.g., `LEFT-INDEX`) to either a relevant motor processor or working memory. Also, to sustain proper performance, this set of rules handles other ancillary bookkeeping, such as starting and stopping the processes associated with Task 1, updating working memory, dealing with stimulus-response repetitions, and so forth.

Complementing the Task 1 production rules, we define a second set of rules for performing Task 2 under the PRP procedure. The Task 2 rules are treated as being totally distinct from the Task 1 rules, and vice versa; neither of these two rule sets "knows" about the content or status of the other. Rather, each set of rules depends solely on the stimulus modality, response modality, number of S-R pairs, and S-R compatibility within the task that it must perform. This modularity constitutes a key aspect of the present models, and simplifies the role played by the coordinating executive process, which is discussed more fully later.

Treatment of S-R numerosity, S-R compatibility, and S-R repetition effects. As mentioned already, various factors may affect the duration of response-selection processes in the PRP procedure and other reaction-time situations (for a review, see Sanders, 1980). To model these effects, we systematically vary the number of production rules, and hence the number of cognitive-processor cycles, used for response selection during a given task. For example, following conclusions from previous studies of S-R numerosity effects (Sanders, 1980), our model's account of the S-R numerosity effect in the study by Hawkins et al. (1979) assumes that performance under their condition with eight Task 2 S-R pairs required more rules than did performance under their condition with two Task 2 S-R pairs. Present accounts of S-R compatibility and repetition effects involve similar assumptions. In particular, the rule sets for both Tasks 1 and 2 incorporate a repetition-by-pass feature such that when an immediate repeat of an individual S-R pair occurs, then the correct response is selected with a reduced number of rule applications. Such treatment is consistent with proposals made by some previous theorists about the source of repetition effects (e.g., see Kornblum, 1973; Pashler & Baylis, 1991; Theios, 1973).[19]

[19] Our treatment of S-R compatibility effects takes a similar tack. We assume that if a task involves compatible stimuli and responses (e.g., right and left arrows respectively indicating right and left keypresses), then a perceptual processor may produce a stimulus-identity code whose features are analogous to ones used by a corresponding motor processor for programming response movements. Consequently, the cognitive processor may pass this code directly to the motor processor, foregoing additional response-selection steps and thereby reducing the total RT. This is consistent with contemporary treatments of compatibility effects (e.g., Kornblum et al., 1990).

Strategic response-transmission modes. A further crucial aspect of the production rules used by our models for performing each task of the PRP procedure is that they can operate in either one or the other of two optional strategic response-transmission modes: immediate, and deferred. With these modes, access to EPIC's motor processors can be managed judiciously, enabling optimal strategies that adhere to task instructions. Also, potential conflicts between tasks that require access to the same motor processor (e.g., a left-hand task and a right-hand task that both need the manual motor processor) can be avoided after their responses are selected.

The *immediate mode* is intended to be used for tasks that have the current highest priority (e.g., in the PRP procedure, Task 1 at short SOAs, and Task 2 at long SOAs). When a task's rules operate in immediate mode, they send the results of response selection (i.e., symbols for selected responses) directly to the relevant motor processor, which then programs corresponding movement features and initiates an overt response without further ado. In essence, this provides one way to implement a high degree of preparation for task completion. Adoption of such an approach may be related to the "sensorial" strategy of performance noted by classical investigators of human reaction time (Boring, 1950; Lange, 1888; cf. Meyer, Yantis, Osman, & Smith, 1984).[20] The immediate mode is invoked by placing the note "`STRATEGY TASK N MODE IS IMMEDIATE`" in working memory and in the conditions of production rules that accomplish response selection. For example, the rule outlined in *Section 3.4* would use immediate mode in selecting a left index-finger response and sending it to the manual motor processor after an 800 Hz tone during an auditory-manual Task 1.

In contrast, the *deferred mode* is intended for performing lower-priority tasks (e.g., Task 2 of the PRP procedure at short SOAs) while higher-priority tasks are underway. When a task's production rules operate in deferred mode, they do not send the symbols for selected responses directly to a motor processor, but instead the response symbols are sent to working memory, which stores them temporarily until an appropriate motor processor becomes available subsequently. This provides a way whereby the production rules of lower-priority tasks may progress on response selection and avoid having their intermediate products disrupt or usurp other unfinished higher-priority tasks. The deferred mode is invoked by placing the note "`STRATEGY TASK N MODE IS DEFERRED`" in working memory and in the conditions of production rules that accomplish response selection. For example, the following rule would use deferred mode in selecting a right index-finger response and sending it to working memory after the digit "2" appears during a visual-manual Task 2.

```
IF
 ((GOAL DO TASK 2)
   (STEP DO CHECK FOR GAMMA)
   (VISUAL DIGIT 2 ON)
   (STRATEGY TASK 2 MODE IS DEFERRED))
THEN
  ((ADDDB (RESPONSE IS RIGHT INDEX))
    (ADDDB (STEP WAIT FOR TASK 2 RESPONSE PERMISSION))
    (DELDB (STEP DO CHECK FOR GAMMA))
    (DELDB (VISUAL DIGIT 2 ON))).
```

[20] According to Lange (1888; cited by Boring, 1950, pp. 148-149), a subject who adopts the sensorial strategy would "direct the whole preparatory tension towards the expected sense impression, with the intention, however, of letting the motor impulse follow immediately on the apprehension of the stimulus, avoiding any unnecessary delay...."

4.2 Specification of Executive Process

In our models of performance under the PRP procedure, progress on Task 1 and Task 2 is assumed to be coordinated by an executive process whose functions are analogous to those of a task scheduler in a multiple-user computer operating system. Such coordination is needed here because the sets of production rules for the individual tasks are independent of each other (*Section 4.1*). If, for example, both the Task 1 and Task 2 rule sets operated in immediate mode at the same time, then this could yield violations of task instructions (viz. premature Task 2 responses) or disruptions of motor processors by conflicting concurrent response symbols. To avoid these potential difficulties, the executive process that we propose for now exerts supervisory control by judiciously inserting and deleting task goals in working memory, monitoring task progress, checking the status of the motor processors, shifting strategic response-transmission modes, and preparing opportunistically for anticipated future movements.

The supervisory control exerted by the executive process has another important benefit as well. It lets our models adapt gracefully to alternative task priorities and knowledge about expected task order. If the instructions are changed to emphasize one task rather than another, or if the degree of certainty about the order of the tasks changes, then this may be accommodated by modifying the executive process, while retaining the same sets of production rules for the individual tasks. This flexibility sets us apart from the rigid response-selection and movement-initiation bottleneck hypotheses considered earlier, which include no explicit provision for supervisory control (e.g., see Keele, 1973; Pashler, 1984; Welford, 1952).

Executive production rules. We specify our assumed executive process in terms of its own set of production rules. The executive rule set is distinct from the Task 1 and Task 2 rule sets in several important respects: (1) As mentioned before, the rules of the executive process can be modified without changing those for performing the individual tasks. (2) The executive rules do not "know" how to perform the individual tasks; rather, their function is to control when the task rules are enabled and what response-transmission mode is used by the task rules. (3). To coordinate progress on the individual tasks, the executive rules take note of residual products left by the task rules and perceptual/motor processors in working memory; the executive rules do not monitor or modify the task rules directly as the tasks are being performed. Thus, a significant degree of autonomy exists on the parts of the different rule sets.

In other important respects, however, the production rules for the executive process are similar to those for the individual tasks. Both the executive and task rule sets reside in EPIC's production-rule memory and are used by EPIC's production-rule interpreter as the cognitive processor proceeds cycle by cycle. Also, the executive rules have the same form as the Task 1 and Task 2 rules (i.e., `IF CONDITION, THEN ACTION`). Like the conditions of the task rules, the conditions of the executive rules may refer to goals (e.g., `GOAL DO DUAL-CRT TASK`), step tags (e.g., `STEP WAIT FOR TASK 1 DONE`), and notes (e.g., `TASK 2 UNDERWAY`) stored in working memory. Similarly, the executive rules' actions manipulate the contents of working memory, adding and deleting items there (e.g., `ADDDB (GOAL DO TASK 2)`, `DELDB (STRATEGY TASK 2 MODE IS DEFERRED)`), and interacting with the individual motor processors (e.g., `SEND-TO-MOTOR OCULAR (PERFORM RIGHT-SMALL)`). For example, how the executive process might begin each trial of a typical experiment with the PRP procedure is illustrated by the following rule:

```
IF
 ((GOAL DO DUAL-CRT TASK)
   (VISUAL CENTER EVENT DETECTED ON)
   (NOT (TRIAL UNDERWAY)))
THEN
  ((SEND-TO-MOTOR MANUAL (RESET))
    (ADDDB (TRIAL UNDERWAY))
    (ADDDB (GOAL DO TASK 1))
    (ADDDB (GOAL DO TASK 2))
    (ADDDB (STRATEGY TASK 1 MODE IS IMMEDIATE))
    (DELDB (STRATEGY TASK 2 MODE IS IMMEDIATE))
    (ADDDB (STRATEGY TASK 2 MODE IS DEFERRED))
    (ADDDB (STRATEGY UNLOCK ON LATE RESPONSE ASPECT))
    (ADDDB (STEP WAIT FOR TASK 1 DONE))
    (SEND-TO-MOTOR OCULAR [PERFORM RIGHT-SMALL))
    (DELDB (VISUAL CENTER EVENT DETECTED ON))).
```

Executive coordination strategy. Exactly what strategy does the executive process use in coordinating Task 1 and Task 2 of the PRP procedure? For present purposes, we propose that it involves an optimal sequence of steps as progress advances on each of the individual tasks. These steps include task enablement, initialization of strategic response-transmission modes, anticipatory eye movements for Task 1 and/or Task 2, monitoring of intermediate perceptual/motor products and task status, unlocking, and final Task 2 movement preparation. An outline of the proposed coordination strategy appears in Figure 10.

Task enablement. At the start of each trial, when an initial warning signal is detected, our proposed executive process enables cognitive processing for both Task 1 and Task 2. This is achieved by putting "GOAL DO TASK 1" and "GOAL DO TASK 2" in working memory. Given these goals, response selection may proceed for each task as soon as its stimulus has been identified and sent to working memory by a perceptual processor.[21] As mentioned already, we assume that the cognitive processor can deal with multiple sets of production rules (e.g., the Task 1 and Task 2 rule sets) at the same time, because of its ability to test and fire them in parallel. Thus, no inherent central response-selection bottleneck is imposed here.

Initialization of strategic response-transmission modes. Another related step performed by our proposed executive process is initializing the strategic response-transmission modes for the Task 1 and Task 2 production rules. Regarding the standard PRP procedure, we assume that at the start of each trial, the executive process puts the note "STRATEGY TASK 1 IS IMMEDIATE" in working memory, setting the Task 1 rule set to immediate mode. Given how this mode works, these rules will then send the identities of selected Task 1 responses directly to the appropriate motor processor, consistent with instructions to make Task 1 be primary. Also consistent with these instructions, the executive process is assumed to put the note "STRATEGY TASK 2 IS DEFERRED" in working memory, setting the Task 2 rule set to deferred mode. As a result, the identities of Task 2 responses selected during the course of Task 1 will be stored in working memory temporarily, rather than going directly to a motor processor, thus ensuring that overt

[21] As implied by the dashed arrows in Figure 10, the executive process does not directly start or stop activities by the perceptual processors for Task 1 and Task 2. Rather, the perceptual processors operate asynchronously, in parallel, with the cognitive processor. Thus, as soon as a test stimulus reaches an appropriate sensor (e.g., the eyes or ears), its perception will proceed autonomously, causing stimulus detection and identification symbols to be sent to working memory. Nevertheless, the activities of the perceptual processors can be controlled indirectly by the executive process, depending on where it directs the focus of the peripheral sensors (e.g., the eyes).

Task 2 responses do not occur prematurely (i.e., before Task 1 responses). Once placed in working memory, a pending Task 2 response must then wait there until the executive process later permits the Task 2 rules to send the Task 2 response to an appropriate motor processor, after progress on Task 1 has advanced far enough that the instructions of the PRP procedure are satisfied and no conflicts occur in the use of the motor processors.

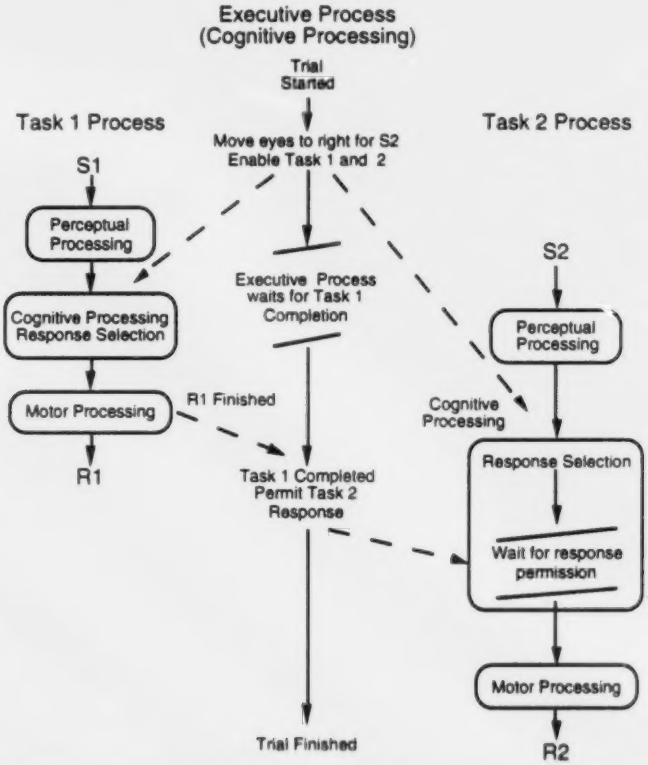

Figure 10. A flowchart that outlines the control structure for a proposed computational model of human performance in the PRP procedure with parallel task and executive processes. Here response selection during Tasks 1 and 2 proceeds simultaneously while satisfying task instructions and optimizing subjects' performance outcomes.

Anticipatory eye movements. Upon putting the aforementioned notes about task goals and strategic response-transmission modes in working memory, our proposed executive process makes anticipatory eye movements (saccades) such that stimulus perception and response selection may proceed as best possible for Task 1 and Task 2. If both tasks involve visual stimuli, and if their stimuli have different spatial locations, then the eyes would first be positioned appropriately for Task 1. After perception of the Task 1 stimulus has progressed far enough, the eyes would be repositioned for Task 2. Alternatively, if only Task 2 is visual, then the eyes would be positioned immediately for it, thereby allowing perception of the Task 2 stimulus to start sooner than might otherwise be the case.

As for manual and vocal responses, we assume that the preparation and execution of saccadic eye movements take significant amounts of time. According to EPIC, this entails

having the ocular motor processor prepare movement features and perform an initiate command, just like the other motor processors do. In particular, saccades might typically involve preparing at least two features, the direction and extent of movement, consistent with results obtained by previous studies of ocular motor programming (Abrams & Jonides, 1988).

Intermediate task monitoring. After its initial preparatory activities, our proposed executive process monitors the progress of performance on Task 1, examining the contents of working memory for information about Task 1's current status, and waiting until further progress has been made on it. During this wait, the Task 1 stimulus occurs, the Task 1 production rules select an appropriate response, and its identity (i.e., the response symbol) is sent to an appropriate motor processor. Depending on the SOA and other relevant factors (e.g., the position of the eyes), progress on Task 2 (i.e., stimulus perception and response selection) may also occur while the executive process waits.

We assume that the executive waiting and monitoring cease when the motor processor for Task 1 sends an efference-copy indicator back to working memory, signaling that production of the Task 1 response has progressed sufficiently far to deem Task 1 "done" (i.e., safe from preemption by Task 2 responses).[2] Given this signal, a Task 1 production rule puts the note "TASK 1 DONE" in working memory, cuing our proposed executive process that it may commence an unlocking process for Task 2. When completed, the unlocking process allows selected Task 2 responses to be sent to their appropriate motor processor for final output.

Unlocking process for Task 2. To be specific, the unlocking process for Task 2 resolves the consequences that stem from Task 2 having started in the deferred response-transmission mode. This resolution involves three phases: *response permission* or *task suspension*, *transmission-mode shifting*, and *task resumption*. An outline of these phases and their time course appears in Figure 11.

Upon noticing that "TASK 1 DONE" is in working memory, our proposed executive process attempts to enter the response-permission phase. Here it checks whether the identity of a desired Task 2 response has already been selected and stored in working memory by the Task 2 production rules. We assume that if this check has a positive outcome, then the executive process grants permission for these rules to forward the response's identity to the appropriate Task 2 motor processor without further delay. Response permission is granted by putting the note "PERMIT TASK 2 RESPONSE" in working memory, which then helps satisfy the conditions of a Task 2 response-transmission rule.

On the other hand, suppose that a Task 2 response has not been selected before unlocking starts. In this case, we assume that the task-suspension phase is entered. Here the executive process temporarily suspends Task 2, briefly precluding further steps toward selecting a Task 2 response. The suspension is accomplished by removing the note "GOAL DO TASK 2" from working memory. This is necessary to facilitate a shift of the Task 2 production rules from the deferred to the immediate response-transmission mode. If response selection for Task 2 were not precluded during this shift, then a selected Task 2 response might be put in working memory at the same time as the Task 2 production rules enter immediate mode, and so the

[2] Under some circumstances, unlocking may start immediately after the Task 1 response symbol has been received by its motor processor. Such early unlocking could occur, for example, if subjects have extensive practice with coordinating the two tasks of the PRP procedure, and if they are highly motivated to produce Task 2 responses as quickly as possible. Alternatively, when subjects are less practiced or less motivated, unlocking may start somewhat later (e.g., after all of the features for an impending movement have been programmed, and an overt movement is about to begin).

selected response could "fall through the cracks," remaining in working memory and never getting sent to its motor processor. By briefly suspending Task 2 response selection in preparation for the shift of response-transmission modes, the executive process ensures that successful "handshaking" occurs between the cognitive processor, working memory, and the motor processors.

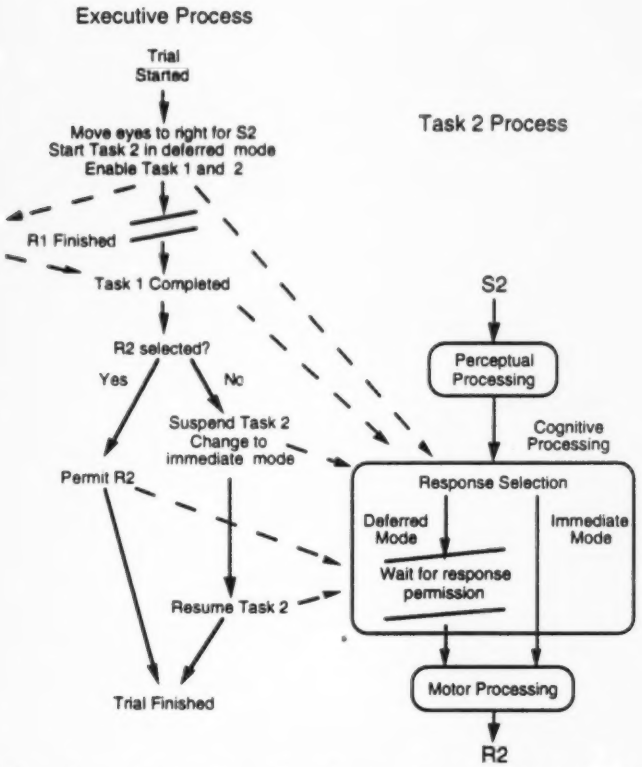

Figure 11. A flowchart that outlines the phases through which the proposed model's executive process goes in "unlocking" response execution for Task 2 of the PRP procedure (cf. Figure 10).

We assume that as soon as the executive process has suspended Task 2, it next shifts the Task 2 production rules from their deferred to their immediate response-transmission mode. The mode shift is accomplished by removing the note "`STRATEGY TASK 2 IS DEFERRED`" from working memory and inserting the note "`STRATEGY TASK 2 IS IMMEDIATE`". Given this shift, future selected Task 2 responses will be sent directly to the appropriate motor processor when Task 2 is subsequently resumed. In effect, the deferred-to-immediate mode shift helps speed the completion of Task 2, once the executive process has determined that the production of responses in Task 2 will no longer preempt Task 1 responses.

The last phase of unlocking is task resumption. It involves reenabling the performance of Task 2 by putting "`GOAL DO TASK 2`" back in working memory. Depending on circumstances at hand, the reinsertion of the Task 2 goal may be preceded by a brief resumption delay, which helps further ensure that task instructions are properly satisfied. Once the executive process has finished the resumption phase, progress on Task 2 -- including motor programming and

movement execution -- can proceed unimpeded.

Anticipatory movement preparation. To facilitate performance after Task 2 has been resumed at the end of the unlocking phase, our proposed executive process takes one further contingent step: movement preparation for the Task 2 response. This step is done if the process of selecting the Task 2 response has not already begun. It involves sending the features of anticipated Task 2 responses to the appropriate motor processor, which then programs them in advance, thereby reducing the amount of time that will be taken in feature programming when the motor processor later receives the complete identity of the selected Task 2 response. For example, if all of the alternative Task 2 responses require finger presses with the right hand, then the executive process may instruct the manual motor processor to preprogram the right-hand feature in advance.

4.3 Similarities to Previous Hypotheses

In summary, our present computational model of multiple-task performance under the PRP procedure has several salient virtues: (1) It adheres to the standard instructions associated with this procedure, which require that Task 1 responses should receive highest priority, and/or occur before Task 2 responses. (2) It ensures that subject to this constraint, Task 2 responses will be made about as rapidly as possible. (3) It is based on mechanisms that, if necessary, can be flexibly modified to obey other instructions and to take account of changes in a priori knowledge about the tasks at hand.

Of course, we do not mean to imply that all of the ideas outlined in this section are entirely new. The executive process proposed here for coordinating Task 1 and Task 2 of the PRP procedure does have some similarities to previous hypotheses about the nature of processing limits associated with human multiple-task performance. For example, at short SOAs, we have assumed that the selection of Task 2 responses proceeds simultaneously with the selection of Task 1 responses, but that the initiation of overt movements in Task 2 may be postponed temporarily by storing selected Task 2 response symbols in working memory, using the deferred response-transmission mode. This is reminiscent of assumptions made before under the movement-initiation bottleneck hypothesis (e.g., Kantowitz, 1974; Keele & Neill, 1978; Logan & Burkell, 1986; Reynolds, 1964). Furthermore, at intermediate SOAs, we have assumed that the executive process briefly suspends the selection of Task 2 responses, in order for the Task 2 response-transmission mode to be shifted from deferred to immediate. During this mode shift, the state of the system would be consistent with assumptions made before under the response-selection bottleneck hypothesis (e.g., Pashler, 1984, 1990, 1993; Welford, 1952, 1959). Thus, in essence, our proposed executive process constitutes an explicit, precise medium for implementing flexible adaptive "allocation policies" like those mentioned by Kahneman (1973) as part of his unitary limited-capacity resource hypothesis (also see Logan, 1985; Norman & Shallice, 1986).

Nevertheless, there are crucial differences between what we propose and what proponents of such previous hypotheses have claimed. Unlike other accounts of multiple-task performance under the PRP procedure, ours does not attribute apparent performance decrements to a limited-capacity central cognitive processor. Rather, we maintain that EPIC's (and people's) cognitive processor may be virtually unlimited in its ability to test and apply multiple production rules simultaneously. Also, for the sake of argument, we maintain that the motor processors associated with different response modalities (e.g., manual and vocal) may function simultaneously. As a result, the PRP effect and other related empirical phenomena are attributed here instead to optional lockout scheduling and alternative response-transmission modes

implemented by the executive process for achieving task priorities and avoiding conflicts within the same motor processor. At a central level, our proposed model incorporates only temporary programmable "soft" bottlenecks, not immutable hard-wired bottlenecks of the sort postulated in both the response-selection and movement-initiation postponement hypotheses.

5. Protocol for Simulations of Performance

To demonstrate the utility of the EPIC architecture and the veracity of the present proposed computational model for human multiple-task performance in the PRP procedure, we have simulated people's RTs under conditions that recreated those in several representative empirical studies. As part of the simulation process, our model was embodied in executable computer programs, which received simulated stimulus inputs, performed specified tasks according to EPIC's theoretical assumptions, and produced simulated response outputs (viz. response identities and latencies). The outputs from the simulations may be evaluated quantitatively by comparing them with actual data obtained during various past experiments on real human subjects.

Software for these simulations was written in the Common LISP programming language. We developed software modules for each component of the EPIC architecture, including its perceptual processors, motor processors, cognitive processor, and working memory. The architecture's processor and memory modules remained the same throughout all subsequent simulations of performance, just as real subjects' basic perceptual-motor and cognitive capabilities presumably would during typical laboratory testing.

5.1 Simulation Steps

Several specific steps were taken as part of each performance simulation that was conducted here:

(1) We chose an important past empirical study with the PRP procedure to be the focus of the simulation (e.g., Karlin & Kestenbaum, 1968). Each chosen study was one whose results bear directly on the validity of our theoretical assumptions versus those associated with the single-channel hypothesis, bottleneck models, and unitary-resource theory.

(2) We wrote an *environment-simulation program* whose inputs and outputs mimicked the task environment of the chosen study. This program simulated the functional characteristics of the study's stimulus displays and response transduction devices. For example, it generated simulated stimulus inputs at appropriate times, and it monitored subsequent simulated response outputs, recording their identities and latencies.

(3) We wrote sets of production rules that performed each of the chosen study's individual tasks and that implemented the executive process through which progress on the tasks was coordinated. The executive and task rule sets -- together with the modules of the EPIC architecture -- constituted a *subject-simulation program* whose operations putatively mimicked subjects' mental and physical activities under the various conditions of the chosen study. Across conditions, the task rule sets changed to characterize the effects of S-R numerosity and S-R compatibility, but the executive rule set typically implemented the same general task-coordination strategy (Figures 10 and 11), except in special cases (e.g., Pashler, 1990, Exp. 2) mentioned later.

(4) For each chosen study, we assigned numerical values to various ancillary parameters used in running the environment-simulation and subject-simulation programs. As much as possible, the parameter-value assignments stayed the same across studies. Further details about these assignments are discussed later.

(5) We ran the subject-simulation and environment-simulation programs simultaneously, having them interact with each other during series of simulated test trials that recreated all relevant details of the chosen study's experimental design. During the simulation run, the components of the EPIC architecture received inputs from and sent outputs to the environment-simulation program; input-output transformations were performed through the cognitive and perceptual-motor processes outlined previously. The simulation run thus generated a simulated replication of the chosen study's empirical data-collection process. In particular, this yielded stochastic (Monte Carlo) distributions of simulated reaction times that constitute our model's account of subjects' performance under various conditions of the PRP procedure.

(6) We analyzed the reaction times produced by the simulation runs, comparing them quantitatively to the actual empirical data reported in the chosen study (e.g., via simulated versus observed PRP curves). This let us assess the extent to which our model fit the data.[23]

In what follows, we discuss more fully some of the details that characterized the present simulations.

5.2 Details of A Typical Simulation

Each empirical study with the PRP procedure on which we focus here included several experimental conditions that differed with respect to the stimulus modalities, response modalities, number of alternative S-R pairs, levels of S-R compatibility, and/or other independent variables. For every such condition, a series of simulated test trials was conducted. This entailed specifying the SOAs, alternative stimulus inputs, and alternative response outputs that could occur during the test-trial series.

Given these specifications, each simulated test trial -- like each trial of the PRP procedure -- involved the environment-simulation program presenting EPIC's perceptual processors with two particular stimulus inputs (i.e., a simulated Task 1 stimulus, and a simulated Task 2 stimulus) sampled from the relevant stimulus set, after which the response outputs (i.e., a simulated Task 1 response, and a simulated Task 2 response) produced by EPIC's motor processors were recorded. In addition, by examining a trace of significant intermediate system states that occurred between stimulus input and response output, we could determine exactly what aspects of our model were responsible for the obtained pattern of simulated response latencies.

Across simulated test trials, the identities of the stimuli varied randomly, as during original data collection in the chosen empirical study. The cycle duration of EPIC's cognitive processor, and other system time parameters, likewise varied randomly from one simulated test trial to the next. This let us mimic stochastic features of actual subjects' performance, as discussed more

[23] At the outset, we have not attempted to model subjects' variations in response accuracy during multiple-task performance. Instead, the present simulations were constrained to produce error-free responses. The initial objective here was to obtain reasonably precise accounts of RT data when response accuracy was high. In principle, however, our model can be extended to deal with patterns of erroneous responses and speed-accuracy tradeoffs, which of course are important for a comprehensive understanding of human multiple-task performance (Luce, 1986; Meyer et al., 1988b, 1988c; Norman, 1981; Pachella, 1974; Reason, 1979).

fully later. We conducted enough simulated test trials that the theoretical means of the resulting simulated reaction-time distributions were estimable with relatively high precision (standard errors on the order of 10 msec or less). Typically, this constraint required on the order of 1000 to 2000 simulated test trials per condition.

5.3 System Parameters

In order for our simulations to run properly, several parameters that influence the dynamics of the EPIC architecture's perceptual, cognitive, and motor processors had to be assigned numerical values on each simulated test trial. Table 2 summarizes relevant information about these parameters. Here we have classified them in terms of their names, the symbols used to denote them, and the system components with which they were associated.

Also shown in Table 2 are the type, mean, and source of each parameter's values. Among the parameters included in our simulations were some whose values either varied stochastically from trial to trial (Type S) or remained constant across trials (Type C). On each simulated test trial, the values of the stochastic parameters were sampled from uniform distributions whose means appear in the next to right-most column of Table 2; these distributions had coefficients of variation (i.e., ratios of standard deviations to means) that equaled 0.2. For some parameters, their means depended on the particular tasks being performed, and their sampling distributions changed across conditions (indicated by "x" entries in Table 2). Other parameters had means that were task independent and did not change across conditions (indicated by set numerical assignments in Table 2).

The means of the parameters in our simulations came from two sources: formal estimates based on results from the chosen empirical studies for which we simulated subjects' performance (Source FE in Table 2); and informal "guesstimates" about what the parameter values might reasonably be (Source IG in Table 2). Where guesstimation of parameter means was involved, their numerical values were assigned through plausible intuitions and/or examination of results from past studies other than those for which performance was being simulated here. This was necessary because some individual parameters in our simulations could not be estimated formally as part of the simulation process (i.e., their values were not separately "identifiable"). Authoritative sources from which we guesstimated some of the parameter values included Atkinson et al. (1988), Boff and Kaufman (1986), and Woodworth and Schlosberg (1954).

Cognitive-processor parameters. The most important parameter associated with EPIC's cognitive processor is the *cycle duration* (t_c). It determines how much time the cognitive processor takes on each processing cycle to test the conditions and execute the actions of all the production rules in EPIC's procedural memory. The rates at which both the individual task processes and the executive process progress depend directly on t_c. As mentioned earlier, t_c is unaffected by the number of production rules that the cognitive processor has to test or fire on each cycle.

On each simulated test trial, we sampled a value of t_c from a uniform probability distribution. The sampling was done independently with replacement. The distribution of t_c did not change as a function of specific task conditions; its mean and standard deviation always equaled 50 msec and 10 msec, respectively. These values were chosen on the basis of results from prior empirical studies that putatively manifest the cyclicity of human information

processing (e.g., Callaway & Yeager, 1960; Dehaene, 1992, 1993; Kristofferson, 1967).

Table 2.
Parameters in Simulations for The PRP Procedure

System Component	Parameter Name	Symbol	Type	Mean	Source
cognitive processor	cycle duration	t_c	S	50	IG
	gating time	t_g	S	25	IG
perceptual processors	stimulus detection time	t_d	S	x	IG, FE
	stimulus identification time	t_i	S	x	IG, FE
	tactile feedback time	t_t	S	100	IG
motor processors	number of features	n_f	C	2	IG
	time per feature	t_f	S	50	IG
	action initiation time	t_a	S	50	IG
	preparation benefit	t_p	S	50	IG
task processes	number of selection cycles	n_s	S	x	IG, FE
executive process	eye refixation time	t_e	S	x	FE
	unlocking onset latency	t_u	S	x	FE
	minimum unlocking duration	t_v	S	100	IG
	suspension waiting time	t_w	S	x	FE
	preparation waiting time	t_y	S	x	IG
external apparatus	response transduction time	t_r	C	x	IG, FE

Note. For the types of parameter listed above, S = stochastic, and C = constant. For the means of the parameters, numerical times are given in milliseconds; "x" indicates parameters whose means changed depending on the conditions for which performance was being simulated. For the sources of the parameter means, IG = informal guesstimate; FE = formal estimate.

Another cognitive-processor parameter related to t_c was a residual *gating time* (t_g). It constituted the amount of time that had to pass before the cognitive processor could use a new piece of information (e.g., a stimulus identity symbol) that had just been deposited in working memory. On average, t_g equaled half of the mean cycle duration (t_c), because of the cognitive processor's cyclic intermittent examination of working memory's contents. In particular, given that the mean of t_c equaled 50 msec (Table 2), the mean of t_g was constrained to be 25 msec.

Perceptual-processor parameters. Supplementing t_c and t_g in our simulations, we included some basic parameters for each of EPIC's perceptual processors. One of these was the *stimulus*

detection time (t_d). It represented the amount of time from the external onset of a presented stimulus until a perceptual processor deposited a corresponding detection symbol for the stimulus in working memory, indicating that the stimulus onset had occurred. During simple-reaction tasks, t_d determined when response selection and transmission could begin. A second basic perceptual-processor parameter was the *stimulus identification time* (t_i). It represented the amount of time from the external onset of a presented stimulus until a perceptual processor deposited a corresponding symbol for the identity of the stimulus in working memory. During choice-reaction tasks, t_i determined when response selection could begin.

For present purposes, the mean values of t_i and t_d were assigned through a combination of both informal guesstimation and formal estimation. We assumed that if the stimulus ensembles used in the tasks of the PRP procedure changed from one condition to the next, then the means of t_d and t_i could too. However, if two (or more) conditions involved the same stimulus ensemble, then the means of t_d and t_i did not change.

Another basic perceptual-processor parameter was the *tactile feedback time* (t_t). It represented the amount of time that the tactile perceptual processor took to sense the overt onsets and offsets of physical responses and to deposit corresponding response-detection symbols in working memory. During all of the simulations reported here, the mean of t_t was constrained on the basis of informal guesstimation to equal 100 msec, consistent with results of past tactile reaction-time experiments (Woodworth & Schlosberg, 1954).

Motor-processor parameters. Some additional numerical values were assigned to parameters associated with EPIC's motor processors. One of these was the *number of movement features* (n_f) prepared by the motor processors when they converted selected response symbols to overt response movements. For present purposes, we typically assumed that n_f equaled 2 (e.g., the number of features needed for specifying the hand and finger to be used in a manual keypress response). Lesser values of n_f were only used when, because of the particular task situation, some response feature(s) could be programmed ahead of time by a motor processor without waiting for response selection to be completed by the cognitive processor.

A second basic motor-processor parameter was the *time per movement feature* (t_f) taken by the motor processors in preparing response outputs. We assumed that the mean of t_f did not depend on either the response modality or the number of features generated during the movement preparation process. Instead, consistent with results of previous research on motor programming (e.g., Rosenbaum, 1980; Meyer & Gordon, 1985), our simulations always set the mean of t_f to 50 msec, the same as the cycle duration (t_c) of EPIC's cognitive processor.

Likewise contributing to the time taken by the motor processors was a third parameter, the *action initiation time* (t_a). It represented an additional amount of time required to initiate an overt movement after all necessary movement features had been prepared. We assumed that during this time, the motor processors initiated overt movement. In all our simulations, the mean of t_a equaled 50 msec, the same as the time per movement feature (t_f).

By adding the action initiation time (t_a) to the product of the number of movement features and the time per feature (i.e., $n_f * t_f$), we generated a *movement production time* (t_m). It represented the total amount of time per trial that a motor processor took to go from a received response symbol to the onset of physical motion for a desired response, assuming the movement

had not already been partially prepared in advance. Because of the means assigned to n_f, t_f, and t_a, respectively, t_m typically equaled 150 msec in our simulations, consistent with results from elementary choice-reaction experiments (Woodworth & Schlosberg, 1954).

If a movement had been partially prepared in advance, then the movement production time, t_m, was reduced accordingly (i.e., by an average of 50 msec per each movement feature already programmed beforehand). The amount of this reduction constituted what we call a *preparation-benefit time* (t_p). For example, when the hand feature for an anticipated movement could be prepared in advance, then the mean of t_p equaled 50 msec.

Task-process parameters. Associated with each rule set for a given task was a task-process parameter, the *number of cognitive response-selection cycles* (n_s) executed per trial during response selection. It equaled the total number of cycles that the cognitive processor spent on selecting the response to a presented stimulus, once the necessary stimulus symbol had entered working memory and the task's production rules were enabled (i.e., the goal of performing the task was in working memory). The mean of n_s varied from task to task, depending on how many S-R pairs were involved and how much S-R compatibility there was within them. In effect, we set n_s by writing production rules that selected responses in ways that were functionally sufficient and consistent with informal guesstimates or formal estimates of how much time response selection actually took.

From the product of n_s and t_c (cycle duration) on each trial, we derived a *cognitive response-selection time* (t_s). The mean of t_s, which likewise varied from task to task, was the average amount of time per trial spent by the cognitive processor on selecting the responses to presented stimuli for a given task.

Executive-process parameters. Five other parameters contributed to the executive process that coordinated performance of the individual tasks. One of them was the *eye-refixation time* (t_e). It equaled the amount of time taken from the onset of a Task 1 stimulus until -- via the ocular motor processor -- the executive process had refixated EPIC's virtual eyes at the spatial location of a visual Task 2 stimulus. For example, if the Task 1 stimulus was auditory, then the eyes could be moved to an anticipated Task 2 stimulus location during the foreperiod of a trial, and t_e could equal zero, thus not affecting the RT produced in Task 2. As shown later, however, if both the Task 1 and Task 2 stimuli were visual, or if fixation on the Task 2 stimulus location was postponed because of other strategic considerations, then the eye-refixation time could dramatically affect the Task 2 RT. We therefore assigned the mean of t_e on the basis of prevailing visual factors and our assumptions about EPIC's ocular motor processor.

The second executive-process parameter was the *unlocking onset latency* (t_u). It equaled the amount of time between two major intermediate events: (1) transmission of a selected response symbol from the production rules for Task 1 to a motor processor; (2) initiation of the shift to the immediate response-transmission mode. In principle, the mean of t_u could depend on various factors, such as how conservative the executive process was in satisfying relative task priorities, and how long the Task 1 motor processor took to send efference copy back to working memory about the forthcoming Task 1 response. We therefore treated t_u as being task dependent; its mean was estimated separately for each of the chosen empirical studies whose results were simulated here.

The third executive-process parameter was the *minimum unlocking duration* (t_v). If the Task 2 response had been selected already and put in working memory through the deferred response-transmission mode, then t_v represented the time between the respective moments when the executive process began unlocking Task 2 and the appropriate motor processor received the identity of the Task 2 response. Alternatively, if the Task 2 response had not been selected and put in working memory by when the executive process started unlocking Task 2, then t_v represented the time that the executive process took to suspend response selection temporarily for Task 2 and to shift from the deferred to the immediate response-transmission mode. The mean of t_v was determined by the executive process's production rules for releasing deferred Task 2 responses and for performing the deferred-to-immediate mode shift. In our simulations, t_v always had a mean equal to 100 msec, because two rules always performed these operations, together consuming two cognitive-processor cycles of 50 msec each. Thus, t_v was task independent.

The fourth executive-process parameter was the *suspension waiting time* (t_w). It equaled an extra amount of time during which the executive process kept the selection of Task 2 responses suspended after the deferred-to-immediate mode shift had been completed. We included this parameter because data from some empirical studies with the PRP procedure (e.g., Hawkins et al., 1979) suggested that Task 2 response selection sometimes remained suspended for longer (e.g., in some cases, 100 msec or more) than the minimum unlocking duration. Thus, the suspension waiting time was treated as a task-dependent parameter, and its mean was estimated on the basis of observed RTs.

Lastly, the fifth executive-process parameter was the *preparation-waiting time*, t_y. It represented an extra amount of time that, depending on the situation at hand, the executive process waited to preprogram some anticipated Task 2 movement feature(s) after Task 2 was unlocked and response selection for it was underway again in the immediate response-transmission mode. The mean of t_y could equal either zero or some positive value as a function of how conservative the system was about producing relatively long Task 2 RTs even after substantial progress occurred on Task 1.

Apparatus parameters. Because we wanted to mimic real subjects' performance as closely as possible in the PRP procedure, our simulations also included an apparatus parameter, the *response-transduction time* (t_r). It equaled the amount of time between the respective moments when an overt response movement putatively began and a recording device would transduce the movement's physical onset. In our simulations, t_r varied from task to task, depending on the modalities of the responses and the types of recording device used to transduce them during the chosen empirical studies. The assumed transduction time was typically greater for vocal responses than for manual keypress responses, because the onsets of audible vocal sounds measured with a voice key are often delayed substantially (e.g, on the order of 100 msec or more) relative to the onsets of the articulatory movements that produce them, whereas finger movements may trigger corresponding switch closures more rapidly (e.g., on the order of 10 msec). Across conditions, the mean of t_r was assigned through a combination of informal guesstimation and formal estimation.

5.4 Formal Parameter Estimation

To estimate the mean values of some system parameters outlined in Table 2, we used a set of theoretical equations that, according to our computational model, characterize simulated Task 1 and Task 2 RTs quantitatively as a function of various experimental-design factors and the SOAs between the Task 1 and Task 2 stimuli. Details of these equations will appear in a forthcoming report (Meyer & Kieras, 1994). Suffice it to say for now that the parameter-estimation process was directed toward achieving two goals: (1) maximizing the goodness-of-fit between our model's outputs and various sets of empirical data from past studies with the PRP procedure; (2) maximizing the degrees of freedom that remained in these data sets for statistical goodness-of-fit assessment after parameter estimation had been done.[24] By pursuing these two goals jointly, our simulations have succeeded at accounting for most of the systematic variance in mean RTs (R^2 on the order of 0.95 or greater) from each of the empirical studies currently under consideration. Furthermore, we have done this without violating the spirit of our original assumptions, without inappropriately fitting residual "noise" in the data, and without exhausting the degrees of freedom available for parameter estimation (Meyer & Kieras, 1994).

6. Results of Simulation Runs

Now let us consider some results obtained from the simulation runs with our computational model of performance under the PRP procedure. In what follows, we present simulations for four different empirical studies whose procedures and data have already been summarized here. To be specific, these studies include ones by Karlin and Kestenbaum (1968), Hawkins et al. (1979), McCann and Johnston (1992), and Pashler (1990).

6.1 Application to Karlin and Kestenbaum (1968)

Figure 12 shows what happened when we applied our model to the previous PRP study by Karlin and Kestenbaum (1968). Here the solid curves represent the observed mean RTs from their Task 1 and Task 2 as a function of the SOA when Task 2 involved either simple or choice reactions. The corresponding dashed curves represent the mean RTs produced during the simulation runs for this study.

As can be seen in Figure 12, the fit between the dashed and solid curves is rather close at virtually all the SOA values. Our model accounts for about 99% of the variance in the observed mean RTs. Both the mean Task 1 and mean Task 2 RTs are well fit. Most importantly, the divergent mean Task 2 RTs for choice reactions versus simple reactions are present in the simulated as well as observed RTs. This holds because, under our model, the executive process permits response selection to proceed concurrently in both tasks when the SOA is short, thereby attentuating the apparent effect of response-selection difficulty on Task 2 RTs at short SOAs, but not at longer SOAs, when Task 2 is performed alone.

These good fits were obtained even though, across the simple-reaction and choice-reaction

[24] For example, one way in which we achieved the latter objective was by keeping many of the mean parameter values (e.g., the stimulus identification times, unlocking-onset latency, minimum unlocking duration, and so forth) constant across conditions of each particular empirical study whose results were simulated. From one study to the next, many of the mean parameter values (e.g., the cognitive-processor cycle duration, number of movement features, movement-production time, and so forth) likewise remained constant.

conditions, the mean values for most of our model's system parameters remained constant. What yielded the systematic differences in the simultated Task 2 RTs across conditions was simply a difference in the average number of cognitive-processor cycles used for response selection, combined with the assumed capability of the cognitive processor to perform response selection concurrently in both Task 1 and Task 2.

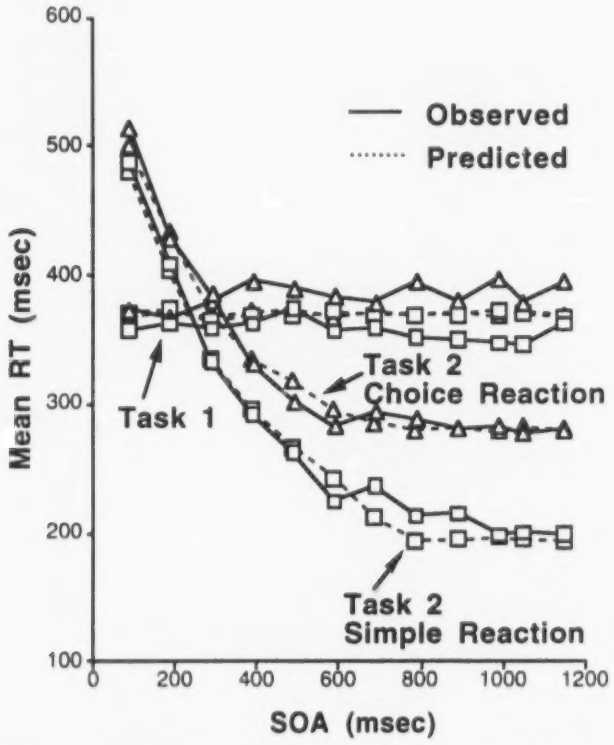

Figure 12. Goodness-of-fit between predicted (i.e., simulated) and observed reaction times for the study by Karlin and Kestenbaum (1968) with the PRP procedure (cf. Figure 5).

6.2 Application to Hawkins et al. (1979)

Similarly, we obtained close fits (on the order of $R^2 = 0.99$) between theory and data in our simulation runs for the PRP study by Hawkins et al. (1979).

Auditory-manual Task 1. For example, Figure 13 shows what happened when our model was applied to the condition of their study in which Task 1 required manual (left hand) choice reactions to auditory stimuli (tones whose pitches varied), and Task 2 required manual (right hand) choice reactions to visual stimuli (digits whose identities varied). Here the observed and simulated RTs have been plotted as a function of the SOA and the number of S-R pairs involved in Task 2. As before (Figure 12), the simulation mimics the apparent interaction between SOA and Task 2 response-selection difficulty, which stems from concurrent response selection for Task 1 and Task 2.

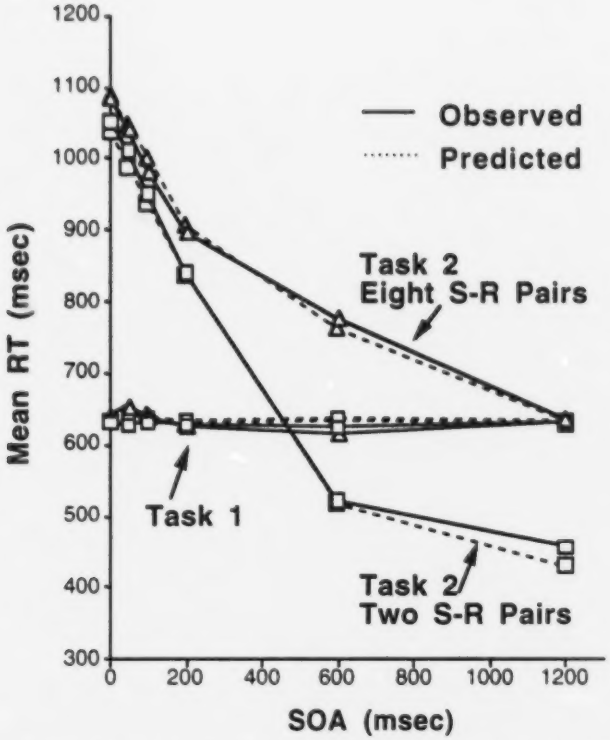

Figure 13. Goodness-of-fit between predicted (i.e., simulated) and observed reaction times for the study by Hawkins et al. (1979) with the PRP procedure using an auditory-manual Task 1 and a visual-manual Task 2 (cf. Figure 7).

Another important point to mention again is that across the various conditions of the study by Hawkins et al. (1979), we kept constant the mean parameter values associated with Task 2 simulus identification and movement production; also, the mean unlocking-onset latency and minimum unlocking duration in our model's executive process remained the same. The only major parameters whose mean values changed as a function of S-R numerosity in Task 2 were the average number of cognitive-processor cycles used for response selection, and the suspension-waiting time taken by the executive process to resume Task 2 after shifting it from the deferred to the immediate response-transmission mode.[25]

Visual-manual Task 1. However, we found one case in the study by Hawkins et al. (1979) for which neither their observed mean Task 2 RTs nor our model's simultated mean Task 2 RTs exhibited an interaction between the SOA and Task 2 response-selection difficulty. This exception occurred when Task 2 was the same as before (i.e. right-hand manual choice reactions to visual-stimulus digits), but Task 1 required manual (left hand) choice reactions to visual stimuli (letters) rather than tones. Here the Task 1 visual stimulus on each trial was spatially separated from the Task 2 visual stimulus by about 5 deg of visual angle. Thus, to

[25] Interestingly, we found that a somewhat longer suspension-waiting time was needed to account for the mean RTs from Hawkins et al.'s condition in which there were eight S-R pairs. This requirement was necessitated by rather elevated mean RTs at the 600 msec SOA, which yielded a PRP curve with a relatively extended "tail" (Figure 13, top curve). Our simulations showed that the extended tail of the PRP curve could not be explained simply through an increase of RT variance across the trials that involved eight S-R pairs.

perform Task 2 after Task 1, subjects had to make an extra intervening saccadic eye movement between the first and second stimulus locations, which introduced an extra delay in the Task 2 responses at short SOAs, because such eye movements take extra time, and stimulus identification -- followed by response selection -- could not begin until after the Task 2 stimulus had been visually fixated.[28]

To model subjects' performance under these latter conditions, we incorporated additional eye movements in the simulations. On each simulated test trial, our model's executive process moved EPIC's virtual eyes from the Task 1 stimulus location to the Task 2 stimulus location after the Task 1 stimulus had been identified. Completion of this eye movement took about 200 msec, starting from application of a production rule that directed EPIC's ocular motor processor to prepare and execute a saccadic eye movement. Thus, at short SOAs, the process of identifying the Task 2 stimulus did not start until substantially later than it had when Task 1 involved auditory stimulus tones instead. Also, the start of response selection was delayed for Task 2 at short SOAs, precluding it from overlapping with response selection for Task 1.

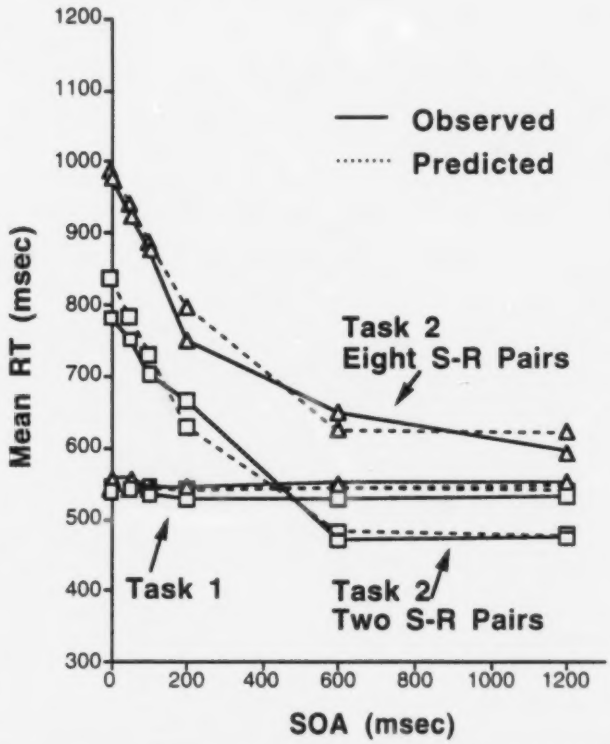

Figure 14. Goodness-of-fit between predicted (i.e., simulated) and observed reaction times for the study by Hawkins et al. (1979) with the PRP procedure using visual-manual Tasks 1 and 2 (cf. Figure 13).

What happened as a result appears in Figure 14. Unlike before (cf. Figure 13), the simulated mean Task 2 RTs exhibited approximately additive effects of SOA and response-selection difficulty (i.e., number of Task 2 S-R pairs). Yet the fit between theory and data

[28] Both the Task 1 and Task 2 visual stimuli were quite small relative to the visual angle that separated them.

remained quite good, because the observed mean Task 2 RTs from Hawkins et al.'s (1979) study also exhibited such additivity. This demonstrates that parallel Task 2 PRP curves may emerge not from a central bottleneck in response selection, but rather from a peripheral perceptual bottleneck associated with the eyes not being able to fixate on more than one place at a time. When experimenters design their empirical studies such that they inadvertently impose the latter sort of bottleneck, then it may be impossible to discover the existence of concurrent response-selection processes that would otherwise occur in multiple-task situations.

6.3 Application to McCann and Johnston (1992)

We believe that perceptual and ocular-motor bottlenecks like those demonstrated in the case of Hawkins et al.'s (1979) study may account for results of many other empirical studies whose experimenters have obtained parallel Task 2 PRP curves and therefrom claimed the existence of central response-selection bottlenecks. For example, consider Figure 15. Here we have plotted observed mean RTs from one of the studies by McCann and Johnston (1992), along with some simultated mean RTs produced by our model. The fit is not quite as good as in some of the previous cases (cf. Figures 12 and 13), but it still seems at least moderately adequate. Most notably, both the predicted and observed Task 2 RTs manifest approximately additive effects of SOA and response-selection difficulty (i.e., compatible vs. incompatible S-R mappings).

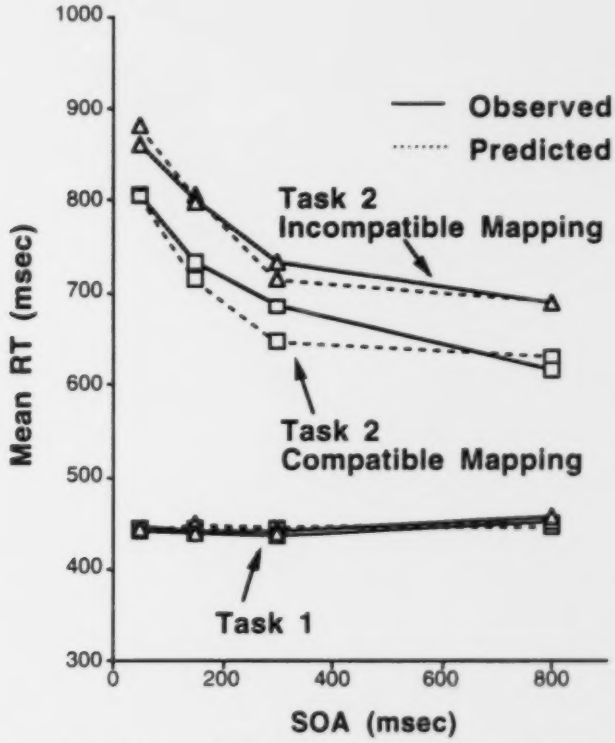

Figure 15. Goodness-of-fit between predicted (i.e., simulated) and observed reaction times for the study by McCann and Johnston (1992, Exp. 1) with the PRP procedure (cf. Figure 4).

To obtain the theoretical outcome shown in Figure 15, we again added an eye movement right before the start of performance on Task 2 at short SOAs. The additional eye movement

postponed the response-selection process for Task 2 long enough that it was precluded from overlapping temporally with response selection for Task 1, thereby yielding additive effects between SOA and Task 2 response-selection difficulty. Given how McCann and Johnston (1992) conducted their studies, it seems likely that the forms of their observed Task 2 PRP curves simply stemmed from the nature of the visual displays there. In particular, they typically entailed unpredictable visual stimulus locations for Task 2 (e.g., McCann & Johnston, 1992, Exp. 2), or other design factors that encouraged extra secondary eye movements (e.g., McCann & Johnston, 1992, Exp. 1).[27] Thus, as in some conditions of Hawkins et al.'s (1979) study, McCann and Johnston's (1992) finding of parallel Task 2 PRP curves does not necessarily support the existence of a central response-selection bottleneck.

6.4 Application to Pashler (1990)

Finally, to illustrate the generalizability of our present model, we have extended it to account for results from the study by Pashler (1990). Here, as mentioned already (Figure 8), the order of the tasks on each trial of a block was either constant or variable; subjects could not always predict what task would come first, but they still had to produce the Task 1 responses first. Consequently, the Task 1 RTs were substantially higher in the variable-order condition than in the constant-order condition. However, across these two conditions, the Task 2 RTs were about the same, and did not differ much from those in a standard PRP procedure.

To account for Pashler's (1990) results, we modified our model's executive process so that its coordination strategy properly obeyed task instructions (i.e., produced responses in appropriate order) despite not knowing what the order of the task stimuli would be. This entailed having the production rules for both tasks operate initially in the deferred response-transmission mode. Such a modification seemed reasonable because it allowed the response order to be controlled more flexibly than when one task's production rules were started in immediate mode.

The aforementioned changes had some interesting consequences. When the SOA was short and the order of the two tasks was not known beforehand, the executive process put the selected response for each task in working memory temporarily, and then decided which response should come first. These extra steps delayed the Task 1 response relative to its onset in the standard PRP procedure. However, the Task 2 response was not delayed much relative to its onset in the standard PRP procedure, because the executive process typically begins Task 2 in the deferred response-transmission mode even if the order of the task stimuli is known beforehand.

As a result, the simulated mean RTs had the pattern shown in Figure 16. Here we have plotted them along with the observed mean RTs that Pashler (1990, Exp. 2) obtained under his constant and variable task-order conditions. The fit again appears quite good. Most notably, both the theoretical and the empirical RTs manifest marked effects of task-order variability on the Task 1 RTs, which are elevated relative to those obtained with constant task order, yet the

[27] More specifically, Experiment 1 of McCann and Johnston (1992) provided subjects with a visual study sheet that outlined the stimulus-response assignments to be used for Task 2. The study sheet was located peripherally relative to the display on which the visual Task 2 test stimuli were presented. Thus, to the extent that subjects focused on the study sheet until Task 1 -- which required auditory discriminations -- was underway, this could have easily introduced extra eye movements before progress on Task 2 began at short SOAs. The likelihood that subjects actually engaged in such behavior is increased by the fact that McCann and Johnston's (1992, Exp. 1) task instructions explicitly encouraged them to use the study sheet whenever need be to facilitate their performance of Task 2.

Task 2 RTs do not change much as a function of constant versus variable task order. According to our model, what enables this good fit is the concurrent response-selection capability of EPIC's cognitive processor. Because of it, Task 2 response-selection processes can proceed as usual in concert with those for Task 1, even though the selection and production of the Task 1 responses are delayed by the task-order variability.

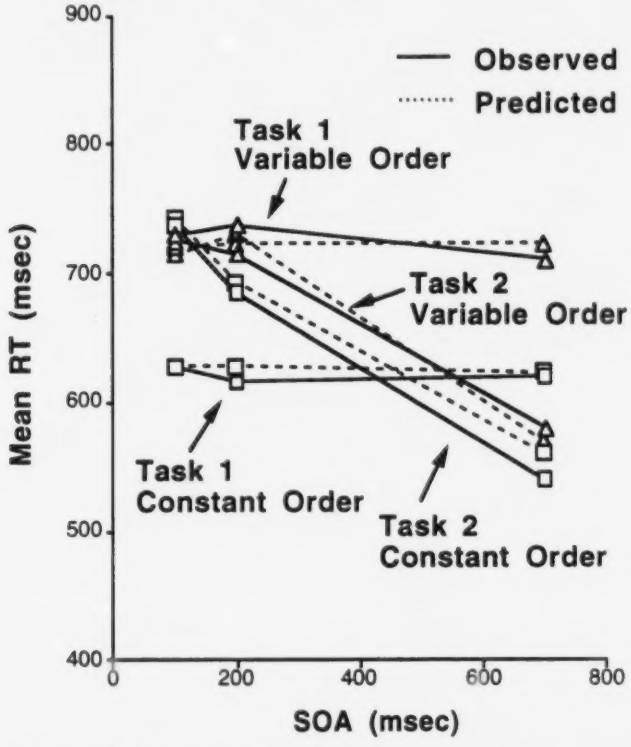

Figure 16. Goodness-of-fit between predicted (i.e., simulated) and observed reaction times for the study by Pashler (1990, Exp. 2) with the PRP procedure (cf. Figure 8).

7. Conclusions

In conclusion, the present research suggests a number of points that may be crucial for future work on human multiple-task performance. Precise principled computational models can help describe and elucidate the temporal relationships among perceptual-motor and cognitive processes used in performing a variety of concurrent tasks. Such models now exist within the framework of the EPIC information-processing architecture. They need have no immutable central-processing bottleneck devoted to only one response-selection or other cognitive operation at a time. Instead, an executive control process may coordinate task performance optimally, exploiting ample central-processing capacity in the face of peripheral structural constraints.

From our theoretical perspective, apparent limits on human mulitiple-task performance have two main sources: people's optional strategic attempts to satisfy task instructions, and perceptual-motor (structural) constraints on the whereabouts of the eyes, hands, mouth, and

other sensors or effectors. Together, these sources may account for empirical data across the diverse conditions included in typical studies with the PRP procedure and its descendants. What we have found also bodes well for extending our approach to more complex task domains and practical applications like those that have previously stimulated some investigators to become interested in human multiple-task performance (e.g., see Wickens, 1984, 1991).

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